Historical Business Cycles and Market Integration: Evidence from Comovement

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Abstract

This thesis addresses historical business cycles and market integration in Europe and America in the 19th and 20th centuries. For the analysis of historical business cycles, the widely used methodology of historical national accounting is complemented with a dynamic factor model that allows for using scarce historical data efficiently. In order to investigate how national and international markets developed since the early 1800s, a multivariate dynamic factor model is used. Spectral analysis helps in measuring frequency specific correlation between financial indicators and rivaling national income estimates for Germany between 1850 and 1913.

One result is that using stock market data helps to discriminate between competing estimates of German national income. A dynamic factor estimated from a broad time series data set confirms this result. Sub-indices for agriculture and industry suggest that the German economy industrialized earlier than evidence from national accounting shows. The finding for the U.S. business cycle is that relaxing the assumption of constant structural parameters yields higher postwar aggregate volatility relative to the period before World War I. Concerning market integration, it is found that European wheat markets integrated faster before mid-19th century than after. Thus, the impact of the metal hull and steam ship as well as the relevance of American wheat for the world wheat market have perhaps been overstated.

Keywords: Industrialization, Business Cycle Chronology, Dynamic Factor Models, U.S. Business Cycle, Market Integration, Imperial Germany

Abstract

Diese Dissertation befasst sich mit europäischer und US-amerikanischer Konjunkturgeschichte und Marktintegration im 19. und 20. Jahrhundert. Zur Analyse von konjunkturellen Schwankungen stellt sie der weitverbreiteten Historischen Volkswirtschaftlichen Gesamtrechnung (VGR) die Methode dynamischer Faktoranalyse zur Seite, die dazu beiträgt, die begrenzten historischen Zeitreihen effizient zu nutzen. Die nationale und internationale Entwicklung von Weizenmärkten seit dem Ende der Napoleonischen Kriege wird mit einem multivariaten dynamischen Faktormodell untersucht. Spektralanalyse wird zur Berechnung frequenzspezifischer Kohärenz von historischen Börsenindizes und konkurrierenden Schätzungen des Nationalprodukts in Deutschland zwischen 1850 und 1913 herangezogen.

Ein wichtiges Ergebnis ist, dass Finanzdaten die Datierung der Konjunktur im Deutschen Kaiserreich erleichtern, was auch durch die Ergebnisse der Faktoranalyse bestätigt wird. Der verwendete Aktienindex, einzelne reale Konjunkturindikatoren und der dynamische Faktor korrelieren eng miteinder. Die Bildung sektoraler Sub-Indizes zeigt, dass der Übergang von einer landwirtschaftlich zu einer industriell geprägten Volkswirtschaft vermutlich früher geschehen ist als Beschäftigungsanteile aus der Historischen VGR vermuten lassen. Die Untersuchung der U.S.-Konjunktur ergibt die Annahme zeitvariierender Strukturparameter eine Erhöhung der Konjunkturschwankungsbreite nach dem 2. Weltkrieg verglichen mit der Zeit vor dem 1. Weltkrieg. Für die Weizenmarktintegration in Europa zeigt sich, dass die Entwicklung vor der Mitte des 19. Jahrhunderts schneller voran ging als danach, was eine Neuinterpretation der Rolle von Technologien wie dem Metallrumpf und dem Dampfschiff sowie dem Eintritt Amerikas als Weizenproduzenten nahelegt.

Schlagwörter: Industrialisierung, Konjunkturdatierung, Dynamische Faktormodelle, U.S.-Konjunkturzyklen, Marktintegration, Deutsches Kaiserreich

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Chapter 1

Introduction

Historical economics may be carried out in several ways, depending on the application of economic theory, and the availability of empirical data. A social historian dealing with a pre-modern subject may choose a purely descriptive approach in order to avoid a priori considerations framing the perception of the past, or, to avoid the danger of anachronistic conclusions. Economic theory may, on the other hand, be perceived as guiding the researcher through complex instances of the past. With the help of empirical data, theories may be confirmed or falsified. The later in history the subject of study is located, the more data is available, which compels the investigator to seek its most efficient usage. Sometimes, new statistical methods are provided by other disciplines, and consequently the wish for more data arises, although it is historically more common that statistical concepts are developed following the availability of new data.

The 19th and early 20th centuries can be described as a period of transition regarding the availability of statistical data. Since about World War II, modern statistics are providing enormous amounts of economic data, often in real time. In contrast to that, before the onset of the nation state, the bulk of economic data only consisted of commodity prices, workers' wages as well as demographic information which often came from church registers. Additionally, data was collected only irregularly. In between those two extremes, the 19th century represents an intermediate period, where the field of statistics developed rapidly, and a large body of economic data was generated – with frequent gaps, however. It is therefore sensible to apply quantitative methods to economic questions of this era, which must be particularly fit to handle scarce data.

This thesis deals in four separate studies with aspects of European and American economic history during the era of industrialization, where data exists but the need to bridge gaps is apparent. It is organized as follows: Chapters 2 and 3 analyze the timing of historical business cycles in Germany between 1850 and 1913, while Chapter 4 looks at cyclical volatility in the U.S. between 1867 and 1995.

Chapter 5 is an analysis of the development of Atlantic market integration during the 19th century. All of these studies reflect recent scholarly debates in economic history, and all are written from a time series perspective.

1.1 Methods

Historical backward calculations of national accounts (HNA) are the major source of historical data employed today. These, however, suffer from lacking data, since not all necessary items for national accounting were collected by contemporaries.

There are broadly three different approaches to calculate national income: the addition of factor incomes (income approach), the sum of private and public expenditures (expenditure approach), and total output of all sectors (output approach). Different problems arise in the historical recalculation of each of these three aggregates. They are often inconsistent, although theoretically they should lead to the same result. Feinstein [1972] proposed to merge rivaling estimates of national income by averaging and forming compromise estimates. This approach, however, may not be helpful, if the competing estimates offset each other at certain points in time, since this may result in biased business cycle timing. Alternative attempts led to the development of analytic tools that circumvent some of the described problems and can handle a wider variety of data. Thus, the present thesis applies spectral analysis and dynamic factor analysis in order to analyze 19th century business cycles and market integration.

These tools follow early attempts to study historical business cycles in the vein of Burns and Mitchell [1946]. They collected hundreds of economic series of all kinds and from all sectors. One research outcome was the grouping of time series into ones that are leading, coincident with or lagging the business cycle. However, this classification does not seem to fit the richness and complexity of the real world. Especially, as the observed time horizon widens, the implied structural stability in dynamic relationships becomes increasingly unlikely. Therefore, formal models have been developed that account for dynamic relations and explicitly assume an unobserved common component. The classic references to be named here are Sargent and Sims [1977] and Geweke [1977]. The theoretical refinement and empirical application are mainly attributed to the pioneering work by James Stock and Mark Watson [Stock and Watson, 1990, 1998, among others].

Dynamic factor models (DFM), as this class of models is often referred to, decompose a set of time series into possibly unobservable common variations f_t and series specific deviations from the common part, u_{it}. This leads to a model of the following form:

$$y_{it} = \lambda_i f_t + u_{it}$$

where y_{it} are the observables, and each λ_i can be interpreted as the observable's sensitivity to the common component or dynamic factor. The dynamic formulation of the factor f_t enables us to estimate both the parameters and the unknown factor via Kalman-filtering.

Today, DFM are widely accepted by empirical macroeconomists. They are used to infer the current state of the economy from large time series data sets, and to make real time predictions. Fortunately, dynamic factor models can easily be applied to historical data.

If one bears in mind the problems of scarce historical data, the application of dynamic factor models to historical business cycles becomes a logical step. DFM deviate from the structural framework of national accounts, and embrace a statistical concept that formulates an intuitive understanding of the business cycle.

But the variety of approaches offered in this thesis is wider. One is to use spectral analysis in connection to financial indicators that are more closely related to dynamic factor analysis than they first appear. Similar to factor models, they can be understood as an aggregation mechanism that reduces a large amount of economic information to a one-dimensional index, which represents the state of the real economy. In Chapter 2 of this thesis a stock market index is compared with national income estimates at business cycle frequencies using spectral analysis. This method allows to decompose a time series into components by frequency, and is therefore a natural choice for this task.

1.2 Results

Chapter 2 uses financial indicators to decide between rivaling HNA estimates of national income in Germany before 1914 [Hoffmann and Müller, 1959, Hoffmann, 1965].[1] The timing of the German business cycle before World War I is a debated issue, since relying on historical national accounts many different stories may be told. For example, it is not clear if the real economy was expanding in the early 1870s or not [Burhop and Wolff, 2005]. According to capital market theory, under the efficient market hypothesis a stock market indicator should be a good predictor of real investment activity. I add real production indices from major industries to demonstrate that real and nominal business cycle indicators moved in accordance with one another. It turns out that a decision between rivaling national income estimates can be made relying on financial and real indicators of investment dynamics. According to this, Hoffmann's [1965] factor income estimate is the superior one.

[1] The paper underlying Chapter 2 is joint work with Albrecht Ritschl. For readability, I will refer only to myself (first person singular) in this introduction. In the following chapters, however, all authors will be addressed if the underlying paper is coauthored.

Relaxing the assumption of capital market efficiency, in Chapter 3, I set up a dynamic factor model to directly investigate real economic activity without referring to historical national accounts.[2] The index of economic activity estimated with the dynamic factor model from a large number of time series [Spree, 1978, 1977] yields a good complement to the results obtained in Chapter 2. The stock market correlates closely with the indicator of economic activity, and precedes it by 1 to 2 years. Furthermore, indices of sectoral activity are formed that allow for studying the process of industrialization from the viewpoint of business cycle comovement. It becomes evident that after the 1850s the German agricultural sector was out of step compared to the rest of the economy. Although its employment share was still more than 50%, agriculture did not act like the overall business cycle, suggesting that sectoral change appears to have occurred earlier than national accounting suggests.

The results of Chapter 3 tentatively anticipate results of Chapter 5 on market integration. The synchronous behavior of regionally dispersed time series before 1840 suggests national market integration in Germany. This is an unexpected finding given the level of political fragmentation at that time.

Chapter 4 deals with a widely accepted stylized fact: the reduction of business cycle volatility in the U.S. (and other developed economies) after World War II.[3] However, the belief that the economic ride was much more bumpy before World War I than in the postwar era may hinge on faultily constructed historical national accounts, as Christina Romer argued [Romer, 1986a, 1988, 1989]. The basic problem is that there is good data on commodity output, but information on the service sector and service components of commodity output such as transport and distribution is lacking [Kuznets, 1946]. The assumption that the overall business cycle changes one for one with commodity output results in an overly volatile business cycle before World War I as claimed by Romer, and contested by Balke and Gordon [1989] and Lebergott [1986]. The room for improvement within the framework of national accounting seems to be small. In this chapter I use an alternative approach along the lines of dynamic factor modeling that explicitly acknowledges the possibility of structural changes over such a long period. The dynamic factor model is therefore extended to allow for time-varying weights of the unobserved indicator of economic activity.

The result is that structural change is the decisive issue. When I tune the empirical model to reproduce results from reconstructed national accounts (which indicate a falling postwar volatility relative to the classical gold standard era), the dynamic factor model assumes the properties of constant economic structures. Compared to that, as gradual structural change is allowed for, the volatility after

[2]The paper underlying Chapter 3 is joint work with Samad Sarferaz.

[3]The paper underlying Chapter 4 is joint work with Albrecht Ritschl and Samad Sarferaz.

World War II increases relative to the time before World War I.

Chapter 2, 3 and 4 present alternative aggregation mechanisms approaching historical business cycle movements in the first and second moments. Moreover, this thesis features in Chapter 5 another natural connection between the economy and comovement – i.e., market integration. Prices in geographically different markets for the same good are expected to move together if information and goods can flow freely. Apparently, they do not always move together perfectly; theory and reality are not congruent. The idea of an unobserved component that is driving observable time series captures this notion. The price in a given market will always reflect to a certain extent supply and demand in other markets. Deviations should be due to the fact that local shocks are too small to be carried over to other markets because of the cost of transmitting information and/or transporting a particular good.

The unobserved component or dynamic factor model in Chapter 5 is extended to capture two processes of price comovement at the same time. The first captures market integration on a world scale, while the second accounts for national market development. I employ wheat price series from 60 cities covering most of the 19th century. The result is that international wheat trade has improved more in the first than in the second half of the 19th century. This finding is in contrast to the established view [O'Rourke, 1997, O'Rourke and Williamson, 1999]. The impact of technologies such as the railroad, steam ship and telegraph is perhaps not as big as assumed so far, and the role of the U.S. on world wheat markets after 1870 may have been overstated.

As a summary, the topics of this thesis are related in the sense that they deal with macroeconomic developments during the era of industrialization in Europe and the U.S. The questions in the different studies presented here reflect current scholarly debates in the economic history community. These are (a) how to date historical business cycles given rivaling HNA estimates, (b) what is the best method to estimate the volatility of historical business cycles, and (c) how can we assess the development of market integration both internationally and nationally? The research strategies chosen to answer these questions aim especially at alleviating the problem of scarce data, which is particularly serious in the 19th century.

Chapter 2

Stock Markets and Business Cycle Comovement in Germany 1850-1913

2.1 Introduction

Among the industrialized countries, Germany compares relatively favorably in terms of our knowledge about national income and output in the 19th century.[1] No less than four different estimates exist that go back to the early 1850s. However, there are major differences between these series regarding their business cycle characteristics.

All available estimates rest on the seminal work of Hoffmann [1965] and earlier work of Hoffmann and Müller [1959]. Hoffmann and his collaborators collected and aggregated a vast amount of data to produce independent estimates of output, expenditure, factor incom-cum-employment, and the income tax base. The inevitable inconsistencies and deviations have generated a literature calling for improvements and corrections of the most obvious problems [Fremdling, 1988, 1995, Holtfrerich, 1980].

Recent work by Burhop and Wolff [2005] represents a systematic attempt to apply these corrections and obtain revisions of all four data series for the pre-1914 period. They also present a compromise estimate, which is a weighted average of their revised series. Their ambitious contribution is intended to put an end to the debate about the main trends of German economic growth in the 19th century and the implied business cycle chronology. However, even the improvements applied by Burhop and Wolff (2005) exhibit business cycle chronologies that are inconsistent with each other. Also, the new compromise chronology they present contradicts the business cycle dating of an older literature that employed disaggre-

[1]International compilations of historical national account data include Maddison [1995, 2001] and Mitchell [2003].

gate evidence, most prominently the NBER business cycle chronology of Burns and Mitchell [1946], as well as related work by Spiethoff [1955].

Among the major industrialized countries, this uncertainty about the business cycle chronology for the later 19th century is unique. Rivaling GNP estimates presented for the U.S. by Balke and Gordon [1989] and Romer [1989] differ in their volatility, but far less so in the business cycle dates they imply. Two independent estimates of British GNP presented by Feinstein [1972] exhibit minor differences in levels but not in the business cycle chronology. In contrast to that, discrepancies between the various German series are so substantial that no consensus view of the business cycle between 1871 and 1913 has emerged so far.

The present chapter sets out to shed further light on this issue by introducing additional information. We refrain from refining one or the other of Hoffmann's series, which, given the improvements made by Burhop and Wolff [2005], would be subject to decreasing returns. Instead, our approach is to exploit the information content in a completely different set of data that has been neglected in the debate so far. This data includes both the stock market and various disaggregate indicators of real activity. After 1870, when the stock market law in Germany was deregulated, a public offering boom set in. It resulted in a ratio of market capitalization to GDP of over 40%, a level that was only reached again in the 1990s [Rajan and Zingales, 2003]. Thus, stock prices reflected information on a substantial portion of the German economy. If the stock market was efficient at the relevant horizons, this information can be exploited to help establish a unified business cycle chronology, and to determine the information content of the rivaling national output series at the business cycle frequencies.

According to established asset pricing models, stock prices should be procyclical and lead the business cycle [Campbell et al., 1997, Cochrane, 2001]. This property also carries over to stochastic growth models with capital. Boldrin et al. [1995, 2001] and Jermann [1998] find that production models with capital adjustment cost and habit persistence provide a good characterization of major business cycle facts. In these models, costly adjustment of the capital stock drives a wedge between the price of existing and new capital goods, inducing a positive correlation between this relative price, or Tobin's q, on the one hand, and investment and output on the other.[2] Under weak capital market efficiency, Tobin's q can be measured by stock prices relative to the price of new equipment (see Hayashi [1982]).

We explore this connection between stock prices and real activity both in the time and frequency domain, focusing on the relevant business cycle frequencies.

[2] Recent work in this tradition includes investment-specific technological change to provide a better rationale for productivity shocks along the business cycle, see e.g. Fisher [2002]. This would strengthen the correlation even further.

To this end, we examine the spectral characteristics of the various national income estimates and apply a bivariate coherency measure to assess the comovement between each series and the stock market. For the pre-1914 world economy, A'Hearn and Woitek [2001] found pervasive evidence of "quasi-cycles" of seven to nine years in GNP and industrial output. We find significant comovement between the stock market and most of the German GNP estimates at similar frequencies. Financial market series for Imperial Germany are nowadays mostly uncontroversial. Research in recent years has produced high-quality stock market series for Germany prior to World War I, notably by Eube [1998] and Ronge [2002]. As each index has its own comparative advantage, we employ them alongside each other.

Ideally, the GNP estimates we want to study would be undistorted measures of output. However, for historical periods, such measures are not to be had. Most available series are either constructed from nominal data using price deflators, or are a convolution of real and nominal series.[3] In a regression of deflated stock market data on deflated GNP series, deflation by price indices on both sides would induce spurious correlation. A related effect occurs in the frequency domain: the patterns of coherency between the time series, as well as the univariate spectral characteristics, are seriously affected by deflating. For this reason, we focus much of our attention on nominal series, both for national product and stock market prices.[4]

Research on Germany's historical national accounts has traditionally argued for a break in data quality around 1890. In that year, income taxation according to modern definitions was introduced in Prussia, and the concepts were soon adapted in the other major states of Germany. Metz [2002] analyzed the frequency domain characteristics of national income estimates based on these tax statistics, and found a pronounced 7-year cycle that extends across the two World Wars. We find that the same series, calculated backwards to 1850 by Hoffmann and Müller [1959], is too smooth before 1890, despite its plausible information on levels. Indeed, income tax assessments before 1890 were based on a moving average of past incomes (see Jeck [1970]), which would help explain this result.

We also find Hoffmann's (1965) widely used estimates of aggregate output and expenditure to perform disappointingly when evaluated against the stock market in the frequency domain. The closest comovement with the stock market is exhibited by nominal wages, a subseries of Hoffmann's [1965] income/employment estimate. Wages trail the stock market by one to two years, and show an impressive comovement with the financial market in the time domain across all cycles between 1870 and 1914. In that period, the German economy experienced six cy-

[3]Historical price indices are themselves highly imperfect aggregates, and in the German case have been criticized in the aforementioned debate.

[4]We will report key results for nominal and real series alongside each other to highlight the effects of deflating.

cles with an average length of 7.5-8 years. These results square well with the findings of Metz [2002] for 20th century Germany, while A'Hearn and Woitek [2001] find a slightly longer cycle in German pre-WWI industrial production data.

Our results are corroborated by inspection of disaggregate indicators of real investment. Wagenführ [1933] and Spiethoff [1955], among others, presented and examined disaggregate indicators of investment like coal and steel production. We show that rather than merely reflecting price level movements, nominal stock prices and nominal wages exhibit substantial comovement with such indicators of real investment and general business cycle activity. Our results clearly support the traditional NBER business cycle chronology for Germany established by Burns and Mitchell [1946], as well as the results of Spiethoff [1955]. At the same time, the compromise estimate by Burhop and Wolff [2005], along with the business cycle chronology they suggest, appears to perform poorly under any of these additional checks.

We present our findings in the following order: In Section 2, a brief presentation of the data follows. Section 3 provides some intuition for our application of spectral analysis. Results are presented and discussed in Section 4. Section 5 concludes and explores avenues for further research.

2.2 Data

We employ two sets of data: the first consists of four different estimates of net national product (NNP), taken from Hoffmann [1965] and Hoffmann and Müller [1959]. The second set of data includes two stock price indices, which we introduce to gain additional information on the cyclical behavior of the German economy under the hypothesis of weak capital market efficiency. Further below, this second set of data will be widened to include sectoral evidence on real investment activity. We take steel production and railroad transport from Hoffmann [1965, p. 352, 417], whereas coal and iron production are from Spree [1978, p. 189, 191].

The NNP series start in the early 1850s. Legislation in 1870 lifted a de facto ban on joint stock companies in most parts of Germany, which implies that meaningful stock price indices are only available beginning in that year [Ronge, 2002] or in 1876 [Eube, 1998]. Thus, only 44 annual data points are available if Ronge's index is employed, and only 38 in the case of Eube's index. This data restriction has important methodological implications, as will be explained later.

2.2.1 The NNP Series

Hoffmann [1965] presented three different estimates of net national income and output, approaching NNP from the output, expenditure and income side, respectively (which is what the series will be named hereafter.) The fourth series in Hoffmann and Müller [1959] is another estimate of NNP from the income side, but employs income tax data to do so. Therefore we call it "Taxes".

"Income" is estimated as the sum of average annual wage and profit rates, weighted by estimated labor and capital inputs. The wage series is mainly calculated from social security contributions, enriched with daily wage data from the Duchy of Baden in south-western Germany, whereas capital income is the estimated capital stock times the return on capital. Hoffmann [1965] originally assumed the return on capital to be constant at 6.68% for the whole period of 1850-1913. Burhop and Wolff [2005] presented an improved profit estimate, which employed a new return series from the dividend yields of joint stock companies. The resulting series yields national income at nominal factor cost. It is commonly deflated by Hoffmann's [1965] implicit NNP deflator. For the purpose of examining each series' comovement with the stock market, we will focus on the wage estimate, as the estimates of profits either exhibit no relevant cyclical dynamics (Hoffmann 1965), or are dependent on the stock market index itself [Burhop and Wolff, 2005].

"Expenditure" is the sum of private and public consumption, investment and exports minus imports. Some components of these series are available in current prices and deflated afterward, while others are first estimated in volumes and then weighted by price indices to arrive at real expenditure. Because of this, it is not possible to entirely filter out the potential bias from deflating. The investment series in this expenditure aggregate is only the annual net change of the capital stock. It is an extrapolation of the capital stock of the Grand Duchy of Baden, derived from capital tax data. This estimate has been severely criticized for its small statistical basis, as Baden is a rather small percentage of the German economy. A first revision of this series was presented by Schremmer [1987]. Burhop and Wolff [2005] applied further revisions, which we adopt here as well.

"Output" is constructed as a volume index of physical production, spliced to an estimate of value added in 1913. The twelve series are weighted by the number of workers in each sector and of census data on the value added per capita in 1936. Burhop and Wolff [2005] use additional employment data and use the new capital stock value for 1913 for their improved version of the "Output" estimate. Since this series was originally constructed from volume indices, it must be inflated to analyze it in current prices.

One entry of the aggregate output series that has recently been subject to major revisions is Industrial Production (IP). Ritschl [2004] revises the income-based metal making and processing series with output data and obtains very different results for post-1913. Burhop [2005] presents a revised IP series up to 1913 that includes additional data and corrections for a number of flaws in the calculation by Hoffmann [1965]. Fremdling [2005] has recently revised the industry census data for 1936. However, these revisions affect mostly the level of output, less so its cyclical behavior, which is of interest here. One possible exception to this is metal making and processing, which is closely related to fixed investment and likely to be heavily cyclical. For this reason, we will later also look at alternative series capturing activity in that sector.

Finally, "Taxes", the series by Hoffmann and Müller [1959], is based on income tax data for all of Germany from 1891 on. For earlier years, data from Prussia and some other states is used. The overall quality of this series is generally considered to be good, beginning in the 1890s. Ritschl and Spoerer [1997] rely heavily on this series in their construction of a long term index of German GNP for the 20th century.

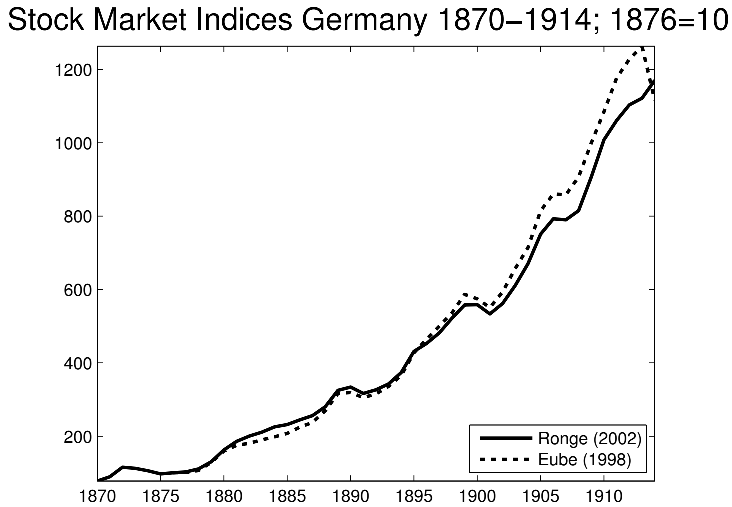
Burhop and Wolff [2005] see this series as the most reliable source of information on GNP levels between 1850 and 1913. Still, prior to 1890 the cyclical information in the "Taxes" estimate of national income seems poor. Following Jeck [1970], we conclude this is due to the tax code prevailing to 1890. Up until that year, income taxes were assessed as a three-year moving average of past incomes. As a consequence, the "Taxes" series is itself a moving average of national income prior to 1890, and hence likely to be flatter than the unknown true data. Unsurprisingly, deflating this artificially smooth NNP estimate leads to a highly volatile real NNP series. This is similar to the spurious volatility phenomenon observed by Romer [1986a, 1989] for U.S. historical data.

2.2.2 The Stock Market Indices

Each of the two stock market series we employ here was constructed for its own particular purpose (Figure 2.1). Ronge's [2002] series is a backward extrapolation of the German DAX index, which includes the 30 most important stocks, annually chosen by their market capitalization. In contrast, the index by Eube [1998] aims to cover as many firms as possible, and thus his index consists of 415 companies in 55 sectors. While the Ronge index is a typical blue chip index akin to the Dow Jones, the Eube index could roughly be compared to the much broader Standard & Poor's 500.

Unfortunately, Eube's [1998] index has three drawbacks. First, it starts only in 1876, which swallows more than 10% of the data points. Second, Eube (1998) does not consider ten of the biggest railroad companies that were included in Ronge's (2002) index, without justifying this decision. Ronge [2002, p. 167] argues that this may be the reason for the relatively bad performance of Eube's index in the 1880s. Railway stocks did relatively well during that period, because of the huge compensations paid to the owners after the nationalizations of the

Figure 2.1: Stock market indices (current prices), levels, Ronge [2002] and Eube [1998].



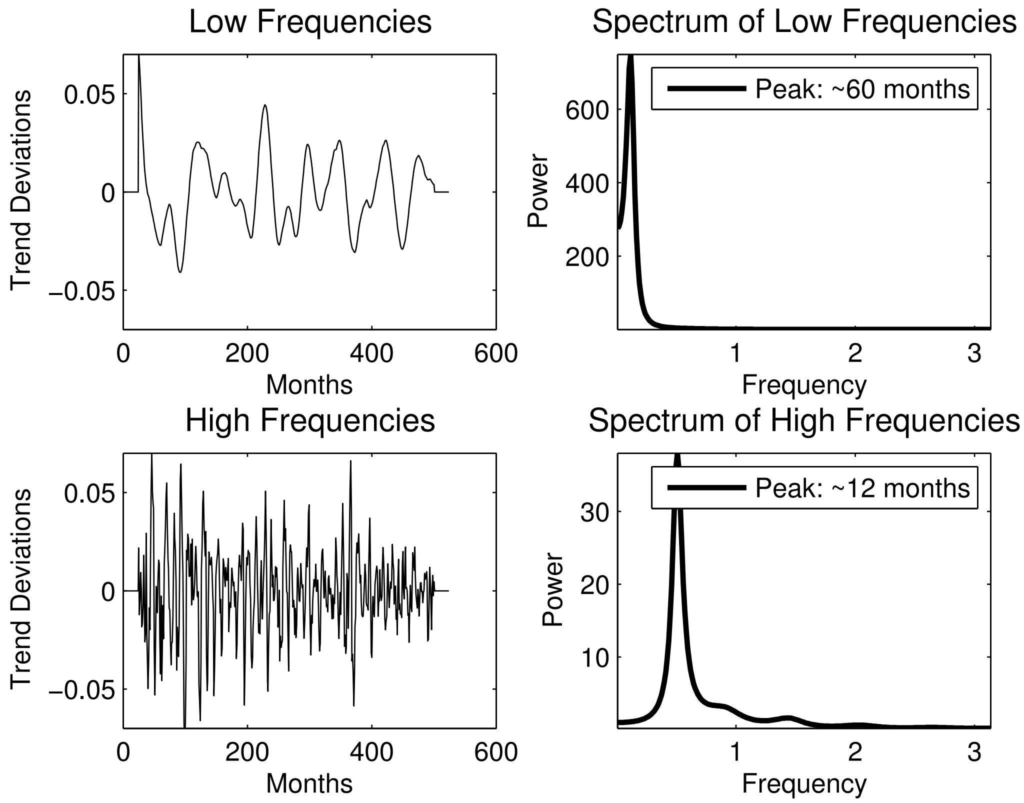
1870s/80s.

Furthermore, Eube [1998] does not account for a component of the yield, the so-called *Stückzins-Usancen*, a fixed interest paid on a stock in addition to dividends. This omission is likely to affect only the intra-year movement of a stock, but we cannot exclude the possibility of bias also at an annual frequency. We will mostly work with Ronge's (2002) index, and use Eube's index only to check for robustness.

2.3 The Tool: Spectral Analysis

Comovements between two series can obviously be measured easily in the time domain by looking at sequences of correlation coefficients. However, we are interested in comovements at the relevant business cycle frequencies; i.e., at time windows of 7-10 years (Juglar) or, to a lesser extent, of 3-5 years (Kitchin). Frequency domain techniques allow us to show correlation differentiated by frequency, and thus to concentrate on the cycles in question. By examining the comovement between NNP estimates and the stock market at these frequencies as a measure of data quality, we implicitly assume capital market efficiency at these frequencies (but not necessarily, for example, in high frequency data). As a check of our results, we also report the pertinent time domain results.

Figure 2.2: High and low frequencies, time and frequency domain.



2.3.1 Basics and Application

According to *Fourier's* theorem, any periodic function can be represented as a (possibly infinite) sum of weighted sine and cosine waves [Priestley, 1981]. One way to express the frequency content of a stochastic discrete time series x_t is to transfer its autocovariance sequence to the frequency domain by multiplying it at every lag k by a complex-valued factor $e^{-ik\omega}$.[5]

$$S_{xx}(\omega) = \sum_{k=-\infty}^{\infty} \gamma(k)\, e^{-ik\omega}, \tag{2.1}$$

where $\gamma(k)$ is the autocovariance sequence of x_t, and i is the imaginary number $\sqrt{-1}$. The result is called *power spectral density* (*PSD*) and is a summary of the frequency content of a time series. It is represented as a graph that peaks at the frequency ω which dominates the series.

[5] According to DeMoivre's theorem, $e^{-ik\omega}$ is another way of writing the sum of sine and cosine waves: $e^{-ik\omega} = cos(k\omega) - i \cdot sin(k\omega)$.

The frequency content of a time series can also be described as the variance of a time series ordered by frequency. Accordingly, the area under the spectrum is the total variance of the series. The area between two specified values of ω then is the share of variance corresponding to a certain range of frequencies, e.g. business cycles of a length between 7 and 10 years.

For our application, we need to look at two time series and their *cross spectral density*. This can be represented as the *Fourier*-transform of the bivariate covariance sequence $\rho(k)$ of the time series x_t and y_t

$$S_{xy}(\omega) = \sum_{k=-\infty}^{\infty} \rho(k) e^{-ik\omega}. \tag{2.2}$$

Cross spectral density is used to obtain the *squared coherency* measure, which is defined similarly to a correlation coefficient as

$$C_{xy}(\omega) = \frac{|S_{xy}(\omega)|^2}{S_{xx}(\omega) S_{yy}(\omega)}. \tag{2.3}$$

Squared coherency shows to which extent x_t and y_t are linearly related to one another, and yields a number $0 \leq C_{xy} \leq 1$ for every ω.

This measure essentially is the frequency domain counterpart to R^2 (the coefficient of determination) that tells us the share of x_t's variance explained by y_t with respect to ω. The total variance of series x, $Var(x_t) = \int_{-\pi}^{\pi} S_{xx}(\omega) d\omega$, can be decomposed into an explained and an unexplained component such that:

$$\int_{-\pi}^{\pi} S_{xx}(\omega) d\omega = \int_{-\pi}^{\pi} C_{yx}(\omega) S_{xx}(\omega) d\omega + \int_{-\pi}^{\pi} S_e(\omega) d\omega, \tag{2.4}$$

where the left hand side is $Var(x_t)$, while the first term of the right hand side is the variance explained by y_t, and the second term is the unexplained variance. In the results section we will use the ratio of explained variance to total variance to obtain the

$$\text{share of explained variance} = \frac{\int_{-\pi}^{\pi} C_{yx}(\omega) S_{xx}(\omega) d\omega}{\int_{-\pi}^{\pi} S_{xx}(\omega) d\omega} \tag{2.5}$$

expressed as a percentage number.

2.3.2 Filtering

Typically, national product series contain a time trend and/or a unit root [Granger, 1969]. In the frequency domain, trends or unit roots are variations with a very low frequency. Series exhibiting these characteristics deviate from the mean more strongly at low frequencies than at high frequencies. Thus, low frequencies request a higher share of the series' total variance. As a consequence, the spectrum of a trended series would always peak at very low frequencies, irrespective of any cyclical behavior. For this reason, many economic time series need to be detrended in order to eliminate the large mass at low frequencies. Done properly, this creates peaks at business cycle frequencies visible in the power spectrum. However, filtering, or rendering a time series stationary, is a difficult task, since it may distort the frequency content of the remaining cyclical part. Simple first-differencing or taking growth rates has proved to severely bias a series toward higher frequencies. Under first-differencing, the peak in Figure 2.2 would artificially be shifted to the right [Hamilton, 1994, p. 177].

For this reason, we will use three filters, and compare the respective results. We use the popular Hodrick-Prescott filter, employing a λ value of 6.25, as recommended by Ravn and Uhlig [2002] for annual data. Canova [1998] and Cogley and Nason [1995] have argued that the HP-filter distorts the frequency content of a non-stationary time series if the series contains a unit root. For this reason, we have also repeated our exercises with a modified version of the Baxter-King filter, which has good properties both in the case of stationarity and non-stationarity [Baxter and King, 1999]. The modification we employ relative to Baxter and King's (1999) filter consists of applying Lanczos' σ-*factors* that solve the problem of spurious side-lobes [Woitek, 1998, A'Hearn and Woitek, 2001]. However, this has the disadvantage of taking away k data points according to the length of the moving-average window. Therefore Christiano and Fitzgerald [2003] designed a band pass filter that nests the filter by Baxter and King [1999] as a special case, but uses the whole sample without taking away data points at either end of the time series. This filter reportedly improves massively over the Hodrick-Prescott filter in real time, but only slightly when historical data is analyzed. Since the Hodrick-Prescott filter is used most often in the literature, for comparability we mainly report those results here, guaranteeing robustness by triple checking with the above mentioned band pass filters.

2.3.3 Estimation of Spectral Density

The definition of *power spectral density* (PSD) given in equation 2.1 requests unlimited data, namely the infinite autocorrelation sequence $\gamma(k)$ for $-\infty \leq k \leq \infty$. In reality we need to approximate this measure by a finite-dimensional estimation.[6]

Non-parametric estimators elegantly calculate the *PSD* directly from the data. Unfortunately, they are inconsistent, but the estimator's variance can be reduced

[6] MATLAB-code for multivariate spectral analysis is available from `http://www.dpmi.tugraz.at/schloegl/matlab/tsa/download.html`.

by averaging over segments of the data. This increases the amount of data needed, rendering them ill-suited for our purpose.

Parametric estimators specify a time series model for the given process, the parameters of which are estimated from the data in the time domain. The parameters are then transformed to the frequency domain. This second method is less data demanding, but depends on the correct specification of the time series model.

Given that our national product and income series are available only at an annual frequency, we face a small sample and thus rely on parametric estimation. Broersen [2000] shows that for small samples, parametric estimators yield better spectral estimates than non-parametric estimators. We will estimate a bivariate vector autoregression (VAR) model, which is the most common approach in the literature. To ensure comparability across our estimates, we employ a lag length of $p = 3$ for all VAR models.[7]

In principle, the VAR-parameters could be obtained by OLS, but we prefer a multivariate version of the Burg method, which yields better estimates than OLS [Trindade, 2000]. It minimizes the mean of the forward- and the backward prediction error.[8]

2.4 Results

2.4.1 Real Series

Table 2.1 shows the relevant correlations in the time domain, as well as comovement for business cycle bands in the frequency domain. The upper panel includes the correlation coefficients between the real NNP estimates and Ronge's [2002] stock market index. We report the lags at which the highest correlation occurs. "Income" has a slightly higher correlation with the stock market than "Taxes" in absolute terms. Note, however, that the correlation coefficient of "Taxes" has the wrong sign: If the stock market is procyclical and leads the NNP series, correlations should be positive at positive lags.

The lower panel shows explained variance, the frequency domain counterpart of the correlation coefficient. Again "Income" fares slightly better than "Taxes" in the 3-10 years band, while in the 7-10 years band, both have 50% higher variance explanation by the stock market than "Output" and "Expenditure". Figures 2.3 and 2.4 show the distribution of explained variance over the respective frequency

[7] All VARs are in filtered data. We experimented with higher order VARs, however with little effect on the frequency-domain results. There are fundamental reasons why this is so, see Priestley [1981].

[8] The multivariate version was developed by Strand [1977] and Morf et al. [1978]. For a discussion of the Nuttall-Strand method, refer to Marple [1987].

Table 2.1: Time and frequency domain correlation between real NNP estimates and Ronge's (2002) stock market index.

Comovement of Stock Market and Real NNP Series

	Output	Expenditure	Income	Taxes
Time Domain				
Corr. (*p-value*)	0.28 (*0.07*)	-0.29 (*0.06*)	0.53 (*0.00*)	-0.52 (*0.00*)
Lag	1	0	3	2
Frequency Domain				
Explained Variance 3-10 y.	0.28	0.30	0.49	0.48
Explained Variance 7-10 y.	0.08	0.08	0.12	0.12

Notes: Lags between NNP and stock prices are in years. All series taken from Burhop and Wolff [2005] and HP (6.25) filtered. P-values for rejection of the null hypothesis of zero correlation.

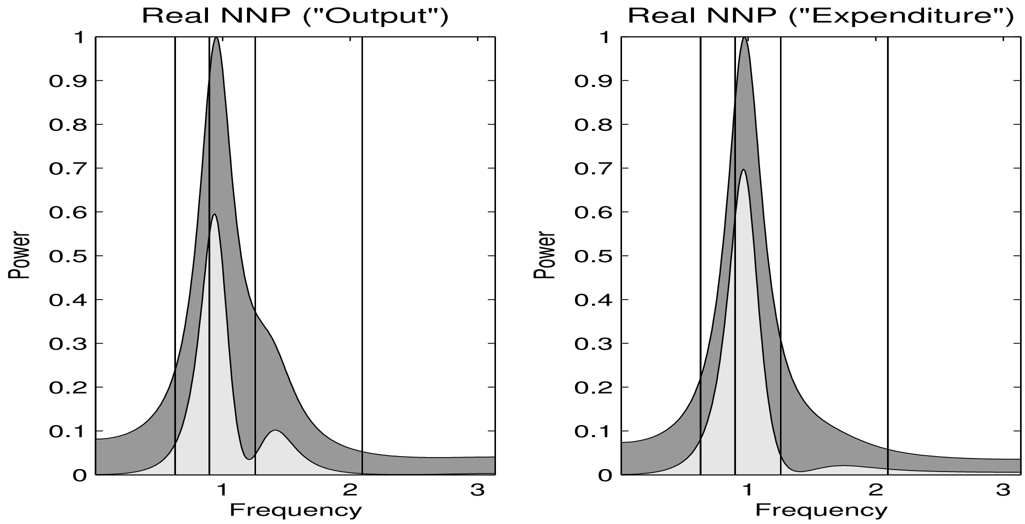
bands, which are respresented as vertical lines. The 7-10 years band lies between the two leftmost lines, the 3-5 years band between the two rightmost ones. Note that "Income" exhibits a clearer peak than "Taxes" and less variance at high frequencies. Summarizing, "Income" estimate exhibits the highest correlation with the stock market, being followed by "Taxes". This result also carries over to the frequency domain when looking at the relevant bands.

2.4.2 Nominal Series

Historical price indices are usually problematic due to lacking observations that make interpolations inevitable. Therefore we plot the nominal and the deflated NNP estimates and the respective HP-filtered versions for visual inspection (Figures 2.5 and 2.6). We observe that the series differ markedly in levels. This is especially true for "Taxes", which starts at a higher level in 1850 than the other series. The implicit smoothing in the construction of "Taxes" is also clearly visible before 1890. The cyclical properties of all three series change markedly after deflating. Again, "Taxes" is affected most. Deflating translates the spurious smoothness of this series in nominal terms into spurious volatility in the real version.

This can be considered to be the German version of the spurious volatility problem in historical time series already described for U.S. data [Romer, 1986a, 1989]. In contrast, deflating the "Income" series appears to reduce its volatility, especially before 1890. In particular, the hump exhibited by the original (nominal) "Income" series in the 1870s almost disappears. "Expenditure" seems to increase in volatility through deflation after 1890, and a marked kink is introduced into the

Figure 2.3: Explained variance of real NNP estimate and Ronge's (2002) stock market index.



time series prior to 1900.[9]

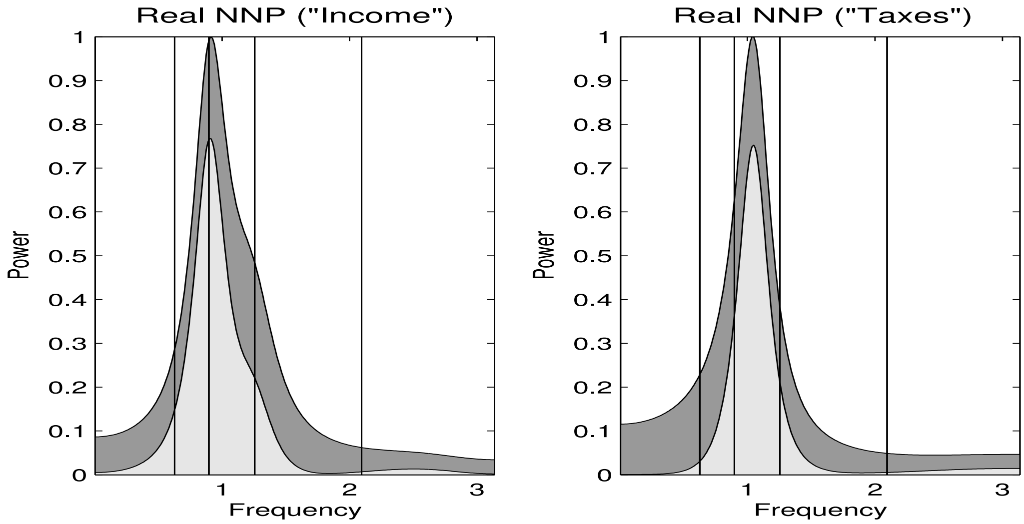
Turning to the cycles around the HP(6.25)-trend (Figure 2.6), it becomes evident that the nominal series exhibit a much clearer picture than the deflated series. There are two reasons for this. First, "Taxes" is up to 60% higher in levels than the other series. Thus, multiplying it with the deflater, which can be as big as 1.74, results in much larger changes. Second, the deflater and "Income" and "Expenditure" partly cancel each other out, so that the variation decreases.

Burhop and Wolff [2005, p. 8ff] focused exclusively on the deflated series, and argued that there may have been a downturn in the early 1870s. Indeed, the deflated "Taxes" series exhibits a downturn around various trend measures. They also notice that "Taxes" exhibits a larger variance than "Income" and "Expenditure" [Burhop and Wolff, 2005, p. 13f]. However, these observations are caused by deflating the nominal series with Hoffmann's [1965] price index that goes up in the early 1870s, and is very volatile before 1880 (Figure 2.7).

The descriptive evidence examined so far suggests that the timing of the cycles in the real series is less than obvious, and that any conclusions about the nature of the German business cycle based on these series alone run the risk of being a figment of the deflation procedure. For this reason, we will also look at the original, nominal series. We will compare the resulting business cycle dating scheme with an average of real business cycle indicators to ensure that the fluctuations we find

[9] Note that we refer to Hoffmann's [1965] series and not to Burhop and Wolff's [2005] revised series to make sure the change is due to deflating alone.

Figure 2.4: Explained variance of real NNP estimate and Ronge's (2002) stock market index.



are not only measuring price level dynamics.

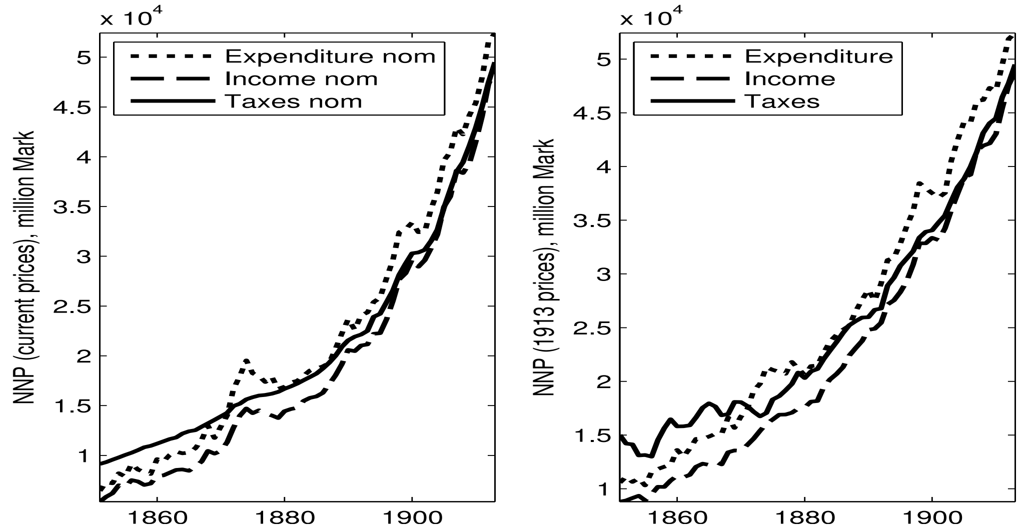
Table 2.2 shows the relationship between the stock market and the three available nominal NNP series.[10] Again, we report results both in the time domain and the frequency domain, where the latter allows us to focus on the relevant business cycle frequencies. Results on the correlation coefficients in the upper panel of Table 2.2 again reveal the close relationship of "Income" with the stock market. In the time domain, it has the highest correlation with the stock market at lag 3 with a correlation coefficient of 0.63, whereas "Expenditure" correlates most strongly at lag -1 (-0.53). Note that "Taxes" now exhibits the correct positive sign, while in absolute terms, its correlation coefficient has practically not changed.

The lower panel of the table differentiates by frequency. Here, we find that a high share of the explained variance of "Taxes" is assigned to non-business cycle frequencies. Only about a third (0.15 of 0.47) can be attributed to the relevant 7-10 years band. In contrast, "Expenditure" and "Income" have about half their explained variance in the relevant frequency band. This is again consistent with the evidence on smoothing in the construction of the "Taxes" estimate. This effect tends to depress both its overall and business cycle coherency with the stock market.

Since "Income" is found to be the series being closest to the financial market benchmark, we now investigate it more carefully. It consists of capital income and

[10]No nominal version of Hoffmann's [1965] "Output" estimate is available from the literature.

Figure 2.5: NNP (current and 1913 prices) Germany 1851-1913.



labor income.[11] Which of these subseries contributes most to the good cyclical properties of "Income"? The corrections applied to "Income" by Burhop and Wolff [2005] left the wage and employment series unchanged but did affect both the capital stock and the return series. Regarding returns on capital, Hoffmann [1965, p. 502] did not attempt to estimate rates of return at all but simply inserted a constant. Burhop and Wolff [2005] instead propose a series that proxies firms' profits by dividends, from which they obtain a series with pronounced cycles.

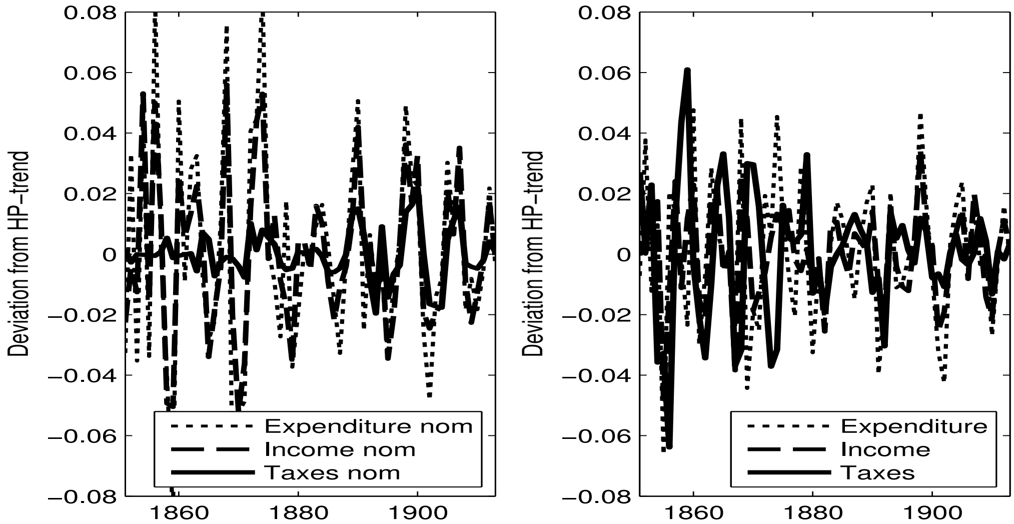
Figure 2.10 shows the cyclical behavior of the new return series. In the 3-10 years frequency band, 63% of the variance are explained by the stock market. This result is hardly surprising, as the return series was derived from dividends. With our research strategy, it must perform well by construction, and therefore contains no information for our purpose.

The construction of the wage series, however, is not connected to the stock market. It was calculated from social security statistics collected in seven single years between 1884 and 1914, interpolated between the benchmarks and extrapolated back to 1850 by daily wages in the Grand Duchy of Baden. Given its shaky statistical basis, there is no a priori reason to assume that the cyclical properties of wages are particularly good. However, we find the coherence between Ronge's stock market index and Hoffmann's wage series to be rather high.

As the right panel of Figure 2.11 indicates, 73% of the variance in wages are explained by the stock market. The explanatory power of the financial market benchmark for wages is thus even higher than for Burhop and Wolff's [2005]

[11]Constructing this series, Hoffmann [1965, p. 510] assumed foreign incomes to be zero. No information on cyclical variations in these missing factor incomes is available from the data.

Figure 2.6: NNP (current and 1913 prices), deviation from trend, Germany 1851-1913.



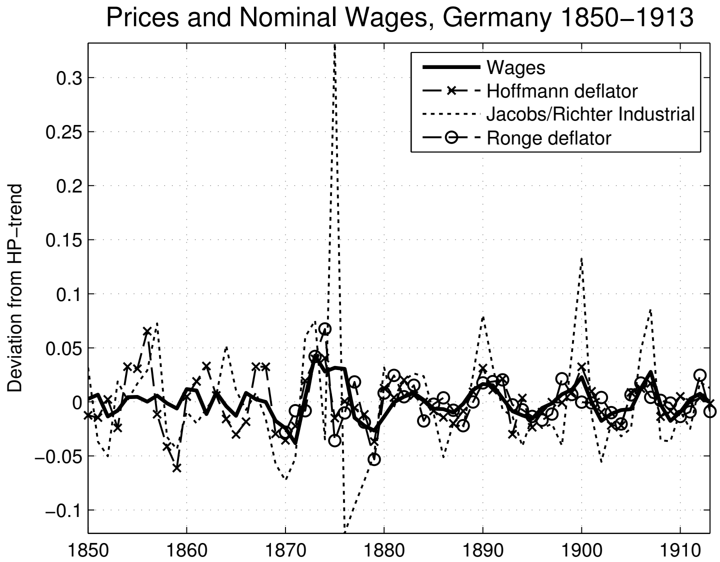
return series, although the latter is connected to the stock market index by construction, while the former is not.

Drawing the results of this section together, we find the comovement of the nominal "Expenditure", "Taxes", and "Income" estimates of NNP with the stock market to be only marginally satisfactory. We do find, however, that there is strong coherence between wages; i.e., Hoffmann's [1965] estimate of the aggregate wage bill, and the financial market. Since wages are constructed independently from financial data, but have similar cyclical properties, we conclude that they should be investigated more closely for business cycle dating.

2.4.3 Nominal Indicators and Real Business Cycles

Before finally proceeding to the business cycle chronology, we must make sure that we are not merely capturing price changes, as both wages, and stock prices are denoted in nominal terms. Figure 2.12 plots HP-filtered stock prices, wages and an equally weighted average of four business cycle indicators measured in physical volumes against each other: iron and steel production, coal production, and railroad transport measured in tons times kilometers. We see that the turning points of our nominal measures are easily confirmed by the indicators of real activity.

Figure 2.7: Hoffmann's (1965) wages series and three price indices



2.4.4 The Business Cycle Chronology, 1870–1914

We begin this section by plotting wages and Ronge's [2002] stock market index along the time axis (Figure 2.13).

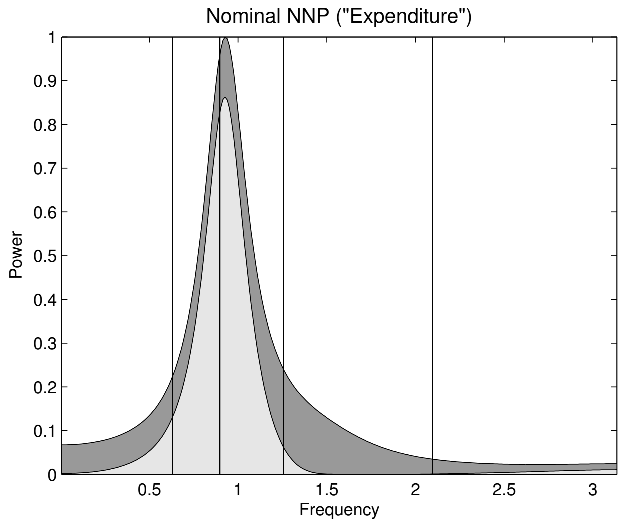
Note that not only do wages and the stock market share a similar cyclical structure in the frequency domain, but they also exhibit a very similar cyclical pattern in the time domain. What matters here is not the amplitude of the cycles but rather the phase of its turning points. In order to make sure that this is not a figment of the data, we repeated the above exercise for Baxter-King filtered series and also include Eube's [1998] index (Figure 2.14).

In Figure 2.14 there is no major deviation from the predominant pattern: Stock markets and wages moved mainly in the same direction, and stocks precede wages by roughly one year.[12] This appears to reflect the blue chip nature of Ronge's index, as well as the exclusion of highly cyclical railway stocks from the broader Eube index (see Section 2.2.2).

The next step is to compare Ronge's stock market index with established business cycle dating schemes and the new scheme proposed by Burhop and Wolff [2005]. Table 2.4 contains peak and trough years of the stock market index, the NBER reference Cycle for Germany, an influential dating scheme by Spiethoff

[12]Differences appear in the volatility of the series. The HP-filtered plot with Ronge's [2002] stock market index exhibits a particularly sharp upswing during the *Gründerzeit* boom of the 1870s (15%) compared to the other plots (∼8%).

Figure 2.8: Explained variance of nominal NNP estimate and Ronge's (2002) stock market index.



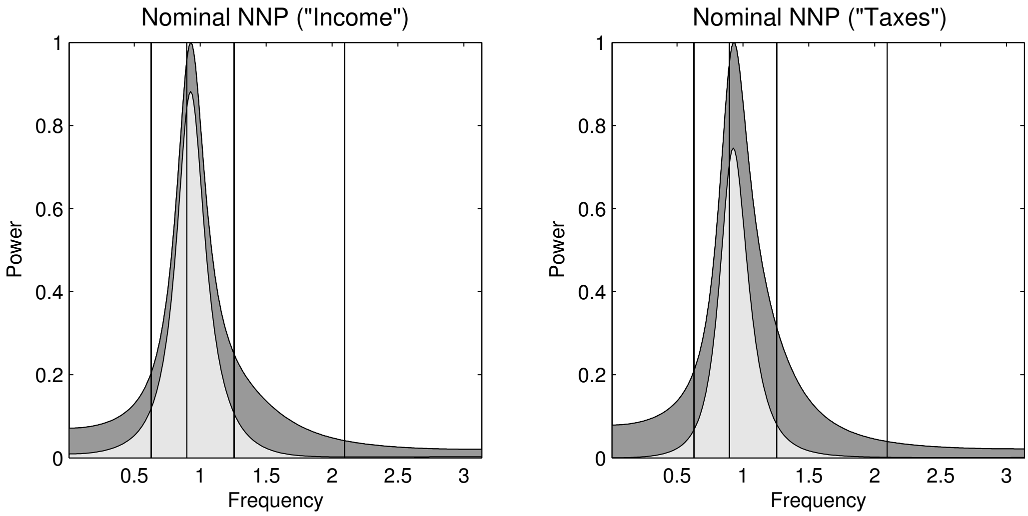
[1955], and Burhop and Wolff's "Compromise"-series. The evidence suggests that the indicator-based dating procedures are in line with the turning points suggested by the stock market index and the Wage series, but differ from the national accounting exercise of Burhop and Wolff [2005].

Except for the additional NBER cycle of 1904-1907 and the last peak before World War I, all peaks and troughs in Ronge/NBER occur at the same year plus/minus one year, which is a very close fit for annual data. Ronge's [2002] stock market index seems to have a slight tendency to lead the NBER reference dates. Spiethoff [1955] finds an additional trough in 1883/84 and a peak in 1906/07, which is two years later than Ronge and NBER. He also finds a peak directly before the war in 1912/13.

Although we already excluded the minor cycles from Burhop and Wolff's [2005] "Compromise"-series, their business cycle dating differs markedly from the chronology established above. They find an additional peak in 1874, right after the *Gründerzeit*-boom, and a trough in 1891. Both phenomena are absent from the chronologies examined above. We also note that their procedure finds no business cycle peak after 1908.

Our results indicate that two forces may be at work in generating this result. First, Burhop and Wolff's [2005] Compromise estimate is the result of averaging series that are partly counter-cyclical to each other or shifted in time. Second, as stated above, some of the series entering the Compromise estimate of Burhop and Wolff exhibit spurious volatility, which appears to carry over to their average series. At the same time, the comparison of our results for the stock market to

Figure 2.9: Explained variance of nominal NNP estimates and Ronge's (2002) stock market index.



the NBER reference cycle shows a striking similarity, which can be understood as a confirmation of the indicator method for 19th century business cycle dating, as opposed to the national accounting approach.

Last, we trace the cyclical behavior of Hoffmann's wages series over time. Bry [1960, p. 139ff] reports evidence of wages lagging the business cycle. Thus, the "true" business cycle turning points may well lie between Ronge's index (a leading indicator) and Hoffmann's average wages (a lagging indicator). If we disregard the slight tendency of the stock market to precede the reference cycle, our chronology moves even closer to the NBER reference points. Except for the troughs in 1871 and 1887, our results then fully confirm the NBER dating. The stock market peak of 1910 should probably be substituted by a later date, since wages peak only in 1912. Table 2.5 shows the chronology which follows from considering wages and the stock market.

Summarizing, the results of this section indicate that there is little, if any need to rewrite the business cycle chronology of Germany in the late 19th and early 20th centuries. Quite on the contrary, we are able to reconfirm the traditional business cycle dating by the NBER and Spiethoff. What we can clearly rule out, however, is a tendency in parts of the recent literature to question the real effects of the *Gründerzeit*/*Gründerkrise* boom and bust of the 1870s on national product [Burhop and Wolff, 2005]. This view was motivated by the deflated "Taxes" estimate of national income. However, we find robust evidence that the deflated "Taxes" series of national income suffers from spurious volatility, induced by the price deflator. Therefore, the cyclical information of this series can largely be

Table 2.2: Time and frequency domain correlation between nominal NNP estimates and Ronge's (2002) stock market index.

Comovement of Stock Market and Nominal NNP Series

	Expenditure	Income	Taxes
Time Domain			
Correlation (*p-value*)	-0.53 (*0.00*)	0.67 (*0.00*)	0.51 (*0.00*)
Lag	-1	3	2
Frequency Domain			
Explained Variance 3-10 y.	0.51	0.63	0.47
Explained Variance 7-10 y.	0.26	0.28	0.15

Lags depict the time shift in years of NNP relative to stock prices. All series taken from Burhop and Wolff (2005) and HP(6.25)-filtered. P-values in parenthesis show the significance level at which the null hypothesis can be rejected that correlation is equal to zero.

dismissed as a figment of the data. Looking again at the various different nominal estimates of national income and product, the traditional business cycle of the 1870s reappears and is alive and well.

As a side result, we are unable to revive the *Great Depression* of the late 19th century. This term originally referred to an older long-swing hypothesis of a downturn between 1873-1896, which for Germany has already been proclaimed dead by Spree [1978] for example. There seems to be no resurrection of the *Great Depression* from our data.

2.5 Conclusions

Business cycle analysis for the 19th century with national accounting methods generally suffers from a patchy database and often inadequate statistical methods. As a result, alternative estimates of doubtful quality lead to conflicting business cycle chronologies. In this chapter, we examine the comovement of financial markets and national income for a number of rivaling series for Germany, applying spectral analysis. Assuming capital markets to be broadly efficient at business cycle frequencies hypothesis, there should be tight comovement between stock markets and the real economy, expressed in the frequency domain by high coherency between the power spectra within business cycle bands. We employ coherency with financial markets as a selection device between the rivaling income series, and construct a new business cycle chronology for Germany between 1850 and 1913.

We find that the real series provided by Hoffmann [1965] and Hoffmann and Müller [1959] suffer strongly from deflating. We therefore focus on nominal series. Among these, Hoffmann's [1965] "Income" series has the highest share of

Table 2.3: Time and frequency domain correlation between nominal wages and capital return and Ronge's (2002) stock market index.

Comovement of Stock Market and Capital Returns/Wage Income

	Capital Returns	Wage Income
Time Domain		
Correlation (*p-value*)	0.87 (*0.00*)	0.74 (*0.00*)
Lag	3	2
Frequency Domain		
Explained Variance 3-10 y.	0.63	0.73
Explained Variance 7-10 y.	0.26	0.38

Lags depict the time shift in years of Returns/wages relative to stock prices. Data: Burhop and Wolff (2005) HP(6.25)-filtered. P-values in parenthesis show the significance level at which null hypothesis can be rejected that correlation is equal to zero.

Table 2.4: Comparison of business cycle dates for Germany 1870-1913.

Peaks and Troughs Germany 1870-1913

	Ronge (2002)		Burns&Mitch. (1946)		Spiethoff (1955)		B.&W. (2005)	
	Trough	*Peak*	*Trough*	*Peak*	*Trough*	*Peak*	*Trough*	*Peak*
1	1871	1872	1870	1872	–	1872/73	1871	1874
2	1878	1881	1878	1882	1878/79	1881/82	1880	1878
3	1887	1889	1886	1890	1883/84	1889/90	1891	1889
4	1893	1899	1894	1900	1893/94	1899/00	1894	1898
5	1902	1904	1902	1903	1901/02	–	1902	1905
6	–	–	1904	1907	–	1906/07	–	–
7	1908	1910	1908	1913	1908/09	1912/13	1910	1908

Spiethoff adapted: Peaks between slumps and booms, troughs between booms and slumps. Burhop and Wolff [2005] also report troughs in 1873, 1877, 1886/87, 1891, 1906, and peaks in 1884, 1893, and 1913, but with lower intensity.

variance explained by a representative stock market index. Its subcomponent, an average wage series for Germany, exhibits surprisingly high coherency with the stock market. To ensure that we are not merely replicating price movement, we evaluate the results against physical indicators of real investment and general business activity, and again find a high degree of comovement.

Our results confirm the traditional NBER business cycle chronology views for pre-war Germany from Burns and Mitchell [1946], as well as the results of Spiethoff [1955]. This also implies that we discard later interpretations that have suggested different chronologies. Among our main findings is the reappearance of both *Gründerzeit* and *Gründerkrise*, the start-up boom and bust of the early 1870s, in the income and output data. However, we are unable to resuscitate the *Great Depression* of the 1880s, which is absent from any of the series we examined.

Our methodology has potential implications for historical business cycle re-

Figure 2.10: Explained variance of Burhop and Wolff's (2005) capital returns and Ronge's (2002) stock market index.

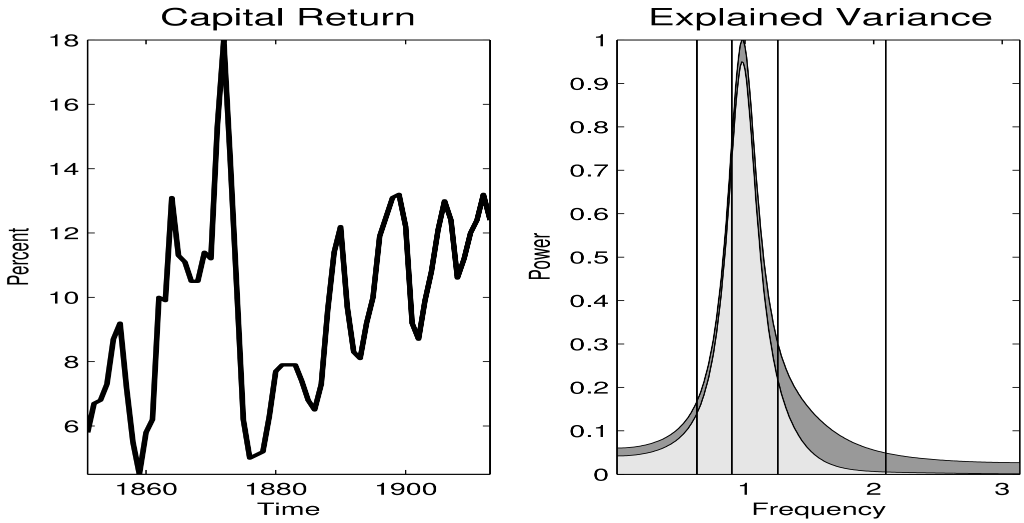


Table 2.5: Business cycles in Germany, 1871-1913.

	1	2	3	4	5	6
Trough	1871	1878	1887	1894	1902	1908
Peak	1873	1882	1890	1900	1905/6	1911

Source: see text.

search, and also lends itself to applications for other countries. We add to a small but growing literature that forgoes reconstructed national account data in favor of the higher information content in contemporary price and volume data on a sectoral level. In the next chapter, the method applied here will be complemented by employing dynamic factor models to reconstruct the business cycle chronology for Germany, further confirming the results of the present chapter.

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Figure 2.11: Explained variance of Hoffmann's (1965) wage index and Ronge's (2002) stock market index.

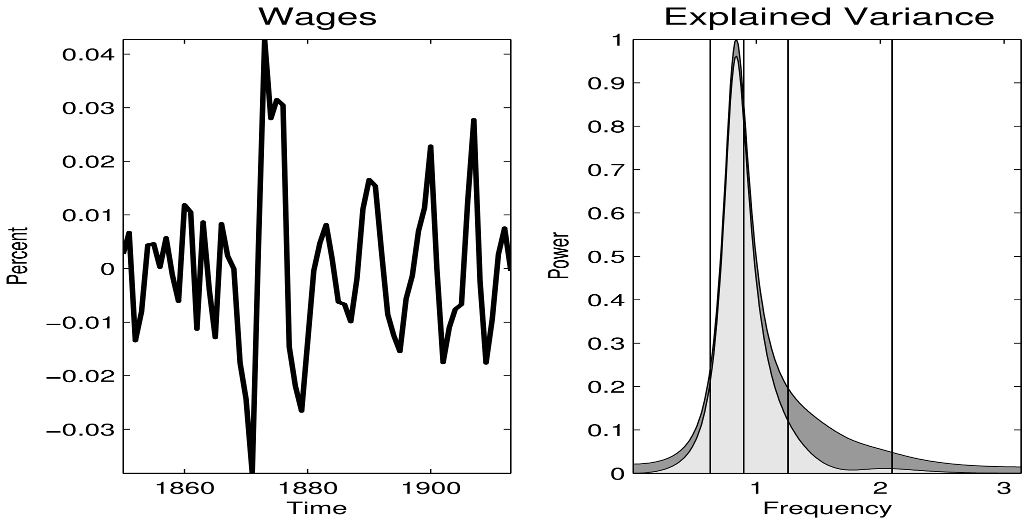


Figure 2.12: Real business cycle indicators (steel, iron, coal, railroad) vs Ronge's [2002] nominal stock price index.

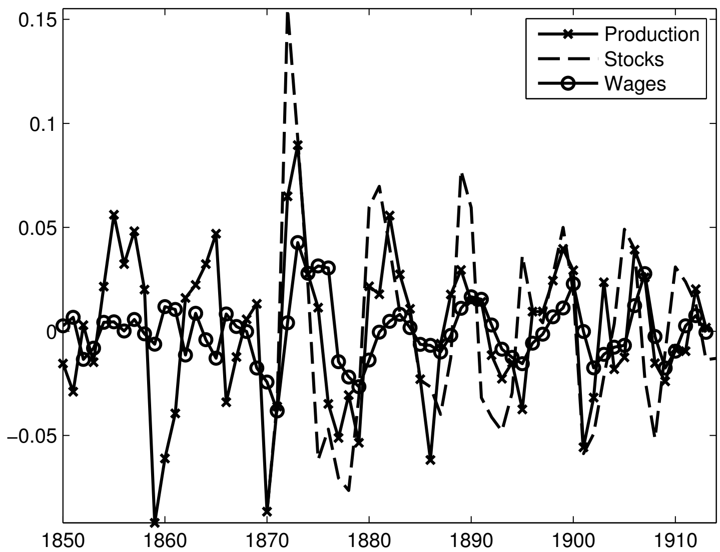


Figure 2.13: The cyclical behavior of Hoffmann's [1965] wage series and Ronge's stock market index in the time domain.

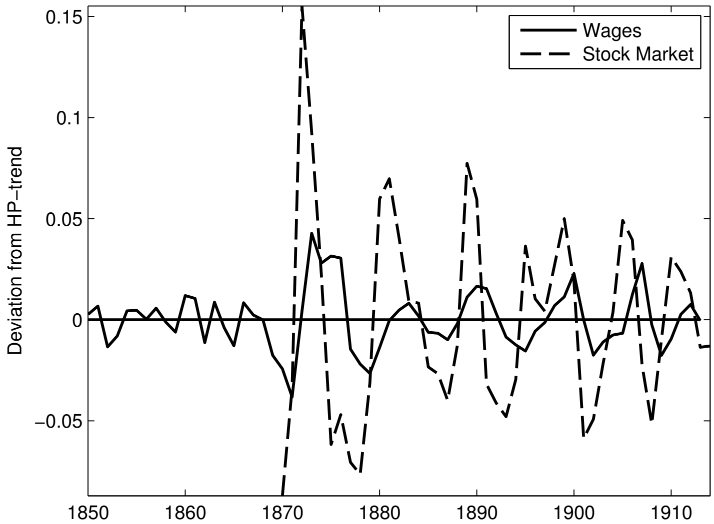
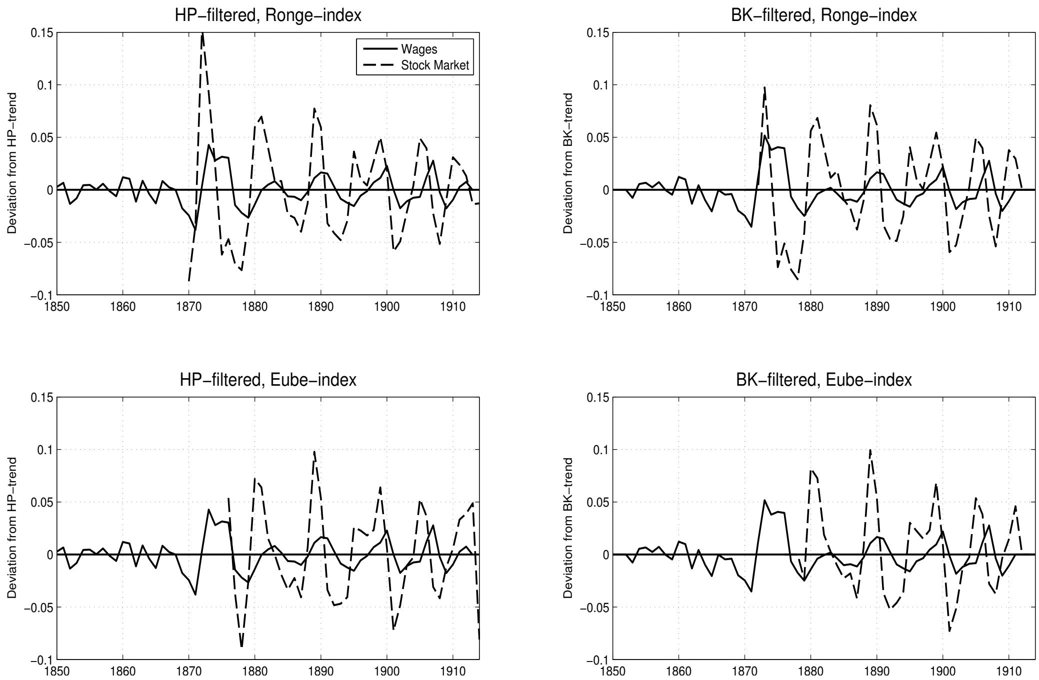


Figure 2.14: Alternative filters and stock market indices.



Chapter 3

A Dynamic Factor Model for Germany 1820-1913

3.1 Introduction

The empirical study of business cycles is very data intensive. While today statistical bureaus, research institutes and other organizations produce endless streams of relevant data, in the 19th century the field of statistics was new, and statistical offices were established only quite late in the industrializing nations (see Tooze [2001] for the German case). Moreover, the first national accounts in the sense of a well-defined measure of a nation's economic output and income were only introduced in the interwar period. In the U.S., for instance, the official annual national income and product accounts began only in 1929. In Germany, the Statistical Office (*Statistisches Reichsamt*) began reporting national income on an annual basis in 1925. Official product and expenditure accounts are only available starting from 1950 for West Germany.

All that we know about national accounts before World War I therefore rests on retrospective reconstructions by later researchers. In Germany, retrospective calculations of national income back to 1890 were presented by the Statistisches Office [1932], and an attempt to construct an index of industrial production was made by the semi-official *Institut für Konjunkturforschung* in 1933, see Wagenführ [1933]. Reconstruction of historical product accounts for the U.S. goes back to Kuznets [1937, 1941, 1946]. His work initiated a large flow of work on reconstructed national accounts, which has dominated the macroeconomic history literature for decades. The main problem with this research has been the lack of data, which was collected only incompletely by contemporary researchers, and in most cases could only partly be recovered later.

As a consequence, results often rely heavily on extrapolations from very few benchmarks, and they tend to differ widely across researchers in terms of business cycle turning points, volatility, or even fundamental growth trends.[1] In this chapter, we offer an alternative method of obtaining evidence on macroeconomic aggregates from the pre-national accounting period. It relies on the NBER business cycle project of Burns and Mitchell [1946], whose philosophy was to collect a large number of disaggregate time series from all sectors of the economy to infer business cycle dynamics.

Modern statistical techniques provide a way to overcome the practical problem that Burns and Mitchell faced, namely, the aggregation of information from the many indicator series. Triggered by the work of Stock and Watson [1990], factor analysis has emerged as an efficient way of providing this information aggregation. In all cases, the underlying idea is the same: individuals, as well as policy makers, regularly observe a large number of highly disaggregate indicators and base their decisions on them. Consequently, a statistical aggregation procedure that uses the information content in these series efficiently should beat national accounts in determining business cycle turning points, forecasting, as well as in monetary policy analysis. Indeed, factor analysis as a means of information aggregation has become quite influential in these areas.

Our contribution is to take the same philosophy back to historical data, where the problem of missing or poor aggregate data is of specific urgency. Furthermore, we propose ways to make inference about structural change and spatial market integration, thereby extending dynamic factor model's natural domain of dating the business cycle. We do so by relying on the central argument of the dynamic factor literature, the comovement between large amounts of sectoral time series.

We believe the way we use dynamic factor models in a rare data environment may be helpful in other fields of historical research. It also has obvious applications in developing countries that do not produce data of sufficient quality and frequency.

Taking Germany as a case study is interesting, because there exist four different national accounting estimates, all differing considerably. That is why the timing of industrialization is an unresolved matter in the German case.

Germany is regarded as an industrial later-comer, based on reconstructed national accounts [Hoffmann, 1965, Gerschenkron, 1962]. Disaggregate time series evidence has been argued to suggest an earlier transition [Spree, 1977]. However, the disaggregate evidence has not been studied with rigorous statistical methods [Spree, 1978, 1977]. In fact, existing studies disagree on the timing of Germany's industrialization [Grabas, 1992, Spree, 1978, 1977, Spiethoff, 1955, Burns and

[1]For the U.S. case, the debate unfolds in Balke and Gordon [1989] and Romer [1989], while reworks of the U.K.'s national accounts appeared by Crafts [1985] and Feinstein [1972], among others. For Germany, Burhop and Wolff [2005] and Ritschl and Uebele [forthcoming], Chapter 2 in this thesis, provide an overview of the revisions to Hoffmann's [1965] national account estimates.

Mitchell, 1946], and were mainly ad-hoc interpretations of the raw data. In contrast, we employ a formal method, a single dynamic factor model (DFM) estimated with Bayesian methods described in Kim and Nelson [1999a]. The latent single factor captures the notion of Burns and Mitchell's [1946] common business cycle in a formal way. The literature originated in the works of Sargent and Sims [1977] and Geweke [1977].

The data consist of a small set of 18 time series ranging from 1820 to 1913, and a large set of 265 time series covering 1840 to 1880 [Spree, 1978, 1977]. Both sets cover many aspects of the German economy, such as production, trade, investment, prices and money supply.

The results obtained by using the entire data set from 1820 to 1913 show that the economic fluctuations were mainly driven by industry. However, when we restrict the analysis and include only data for the first half of the century, agriculture plays the expected dominant role in driving cyclical fluctuations.

We observe comovement between different regions and industries even before 1840. Given Germany's late political unification, this evidence for economic integration is interesting.

Concerning Germany's business cycle history, we do find clear evidence for the "Gründerzeit" or startup boom of the early 1870s, which has often been described as a remarkably prosperous period.[2] Yet there is the claim that spurious net national product data may have incorrectly contributed to that notion [Burhop and Wolff, 2005]. This discussion touches upon an important part of German history. Was the foundation of the German nation state really accompanied by a broadly based economic upturn? Our latent factor peaks in 1873, and it covers a wide array of industries. Indeed, construction can be identified as one of the main driving forces. It seems that public opinion in this case need not be corrected.

The robustness of our business cycle dating is confirmed by evidence from financial markets. We examine the comovement between the latent factor and a stock market index that includes the largest German companies and is not included in our data. We find that the index almost perfectly tracks the cyclical behavior of the factor and precedes it by 1 to 2 years.[3]

In summary, the main contribution of this chapter is to introduce Bayesian estimated dynamic factor models into the historical business cycle literature and, in doing so, complement the historical national accounting approach. We propose methods for analyzing sectoral transition and market integration, based on comovement.

In the following we give an intuitive introduction to dynamic factor models

[2] On the history of the German Empire see Wehler [1985] and Stern [1977].

[3] This is well in line with the predictions of capital market theory, see for example Cochrane [2001].

and motivate our methodological choice from our research questions. We then describe the factor model and its estimation formally, present the data, and finally discuss the results in detail.

3.2 Motivation

3.2.1 Intuition of the Model

In this section we set out the broader historiographical context of the chapter in order to develop our research questions and motivate the choice of a dynamic factor model to approach them. We start with an intuitive illustration of dynamic factor models.

Mills and Crafts [1996] described an unobserved-components model in a well-known paper:[4]

$$y_t = \mu_t + \psi_t, \tag{3.1}$$

where the log of industrial production y_t is decomposed into an unobserved trend component μ_t and an unobserved cyclical component ψ_t. The trend component μ_t is modeled as a stochastic linear trend and the cyclical component follows an AR(q) process with $q = 2$.[5] To extend this framework, let $\widetilde{y}_t = [y_{1,t}\ y_{2,t}\ \ldots\ y_{N,t}]'$ be a vector with N elements and let μ_t and ψ_t be scalars.[6] In this case we can re-write Equation (3.1) as:

$$\widetilde{y}_t = 1_N \mu_t + 1_N \psi_t, \tag{3.2}$$

where 1_N is a $N \times 1$ vector of ones. According to Equation (3.2) μ_t would be the trend component common to all N variables and ψ_t would be the common cyclical component. Since we work with stationary data, we can drop the common trend component and add an error term to Equation (3.1), representing the part of vector y_t which could not be captured by the common cycle ψ_t. Redefining $\psi_t \equiv f_t$ and replacing the 1_N vector with a $N \times 1$ parameter vector Λ we obtain the dynamic factor model used in this chapter. It divides the observables into a common part f_t and a series specific part. A detailed description and how this class of models can be estimated follows in Section 3.3. A short scratch of the historical background may motivate why this model could contribute to scholarly knowledge about the economic history in Germany between 1820 and 1913.

[4] For more historical applications of such state-space models see Solomou [1998].

[5] For a more detailed description of the model we refer to Mills and Crafts [1996].

[6] As an example, assume $N = 4$ and logged data on industrial production, personal income less transfer payments, total manufacturing and trade sales. This is exactly the data set used for the dynamic factor model in Stock and Watson [1991].

3.2.2 Historical Background

The economically relevant parts of Germany's history in the 19th century are plentiful, diverse and complex. We focus on the aspects that are relevant to develop the research questions we want to address in this chapter.

For rhetorical reasons we may choose "change" as the overarching theme of Germany's 19th century economic history; change with respect to almost any aspect of public life. Six major aspects should be named here, starting with the transition from a politically fragmented conglomerate of independent states that emerged from the Napoleonic Wars to the foundation of the German Empire in 1871. This reshaping of the political landscape led to monetary integration, unified weights and other units, a formulation of national trade policy, and the gathering of political parties representing nationwide economic interests, among others.

A second aspect which is closely related to the first is the gradual widening of a zone without internal tariffs, which developed – at least formally – into the first nationally integrated market between the Alps and the North and the Baltic Sea.

In addition to the abolition of institutional trade barriers, transport technology underwent a revolution. The most important innovation was the railway, but inland navigation was also relevant.

The transport revolution may be central in today's public perception of the era of industrialization – hand in hand with the development of industrial centers such as the Ruhr valley, Berlin, Silesia and Saxony. The weight shift between rural and urban regions was the source to radical changes of the employment structure and living conditions as the masses fled the countryside [Fremdling, 1975].

Related to the new capital intensive production methods was the development of highly sophisticated financial markets that organized the interaction between investors and entrepreneurs. Joint stock banks became a major instrument to finance railroad companies and mining industries [Guinnane, 2002]. Stock markets experienced a major boost after the liberalization of stock market legislation 1870/71 [Baltzer, 2007, Eube, 1998]. So-called universal banks engaged in retail as well as investment banking and are allegedly responsible for Germany's catching up with the U.K. in the second half of the 19th century [Gerschenkron, 1962, Fohlin, 2007].

Last but not least, the demographic transition shall be named. In accordance with those of other industrializing nations, Germany's population grew rapidly, despite the population reducing effect of emigration to western offshoots such as North and South America.

3.2.3 Research Questions and Reasons for DFM

Having outlined the changes in Germany in the 19th century, the questions we want to address here derive as follows.

Concerning the aspects of political fragmentation, the transport revolution and the creation of the customs union (*Zollverein*, ZV), the question arises as to how and when economic integration in Germany was achieved. This question has been of course addressed by others, such as Fremdling and Hohorst [1979] and Keller and Shiue [2007]. However, when estimating an index of economic activity that is defined by the comovement of its underlying economic series, some evidence for economic integration is almost inevitable. As our data for the first half of the 19th century are partially regional and do not cover the whole region that from 1871 on formed "Germany," finding a common cycle among regionally different series would be a strong sign of economic integration.

The second question concerns the timing of the business cycle in the presence of about half a dozen different opinions that can be found in the literature [Ritschl and Uebele, forthcoming, Burhop and Wolff, 2005]. Dynamic factor models could take the discussion a step forward because they can employ more information than historical national accounts.

In particular, they can employ more information, because series that contain information about the state of the economy, such as financial and demographic series, often cannot be used in national accounting as they do not fit into the national accounting framework. This applies explicitly to nominal time series, which – if prices are determined by the market – contain information about relative scarcity and therefore indicate changes of the state of the economy. In this sense DFM use the available data more efficiently as less data must be left unused.

To a certain degree DFM can even make up for bad data quality. The argument is that measurement errors are by definition unsystematic and therefore series-specific. As DFM are designed to identify comovement, they will extract the signal of a data series although it contains large amounts of noise.[7]

A final third research question tries to capture the theme of change that characterizes the whole period. Historical national accounts need to be created year by year to present a picture of a changing economy; an impossible task from hindsight and therefore only approximated as well as possible. Dynamic factor models need only time series as input and deduce patterns of economic change from their interplay. This is captured by the spectral density matrix that describes the linear relationships between the series at all leads and lags.

[7]Our experience is, however, that this relationship suffers from decreasing returns. At some point adding more data may even add so much noise that the underlying signal is extracted worse than before but we are confident that the present project is still in the zone of positive returns as data input is low.

In this chapter we specifically compare the sub-sectoral indices of sectoral activity with each other, which we believe has not been done before in that form. We develop changing comovement between economic sectors as an argument for structural change. For example, an index of agricultural activity should comove with the index of industrial activity as a necessary condition for shock transmission. If comovement is not found, we conclude that those sectors are not strongly affected by respective sectoral shocks. This may allow for something to be said about the timing of the transition from agriculture to industry as the leading sector in Germany.

3.3 Formal Model Description and Estimation

Dynamic factor models in the vein of Sargent and Sims [1977], Geweke [1977] and Stock and Watson [1990] posit that a given panel data set can be divided into a latent common component, which captures the comovements of the cross-section and a variable-specific idiosyncratic component. These models imply that macroeconomic activity is driven by a few latent driving forces, which can be represented by the estimation of the dynamic factors.

Our data set consists of individual time series $y_{i,t}$ for $i = 1,\dots,N$ and $t = 1,\dots,T$, with N and T representing the total number of cross-section variables and the length of the time series, respectively. DFM assume that this data set can be described with the following equations:

$$y_{i,t} = \lambda_i f_t + u_{i,t}, \tag{3.3}$$

where f_t represent the latent common factor or activity index, λ_i is the factor loading or coefficient linking the common factor to the ith variable, and where $u_{i,t}$ is the variable-specific idiosyncratic component.[8] For the factor we assume an AR(q) process:

$$f_t = \phi_1 f_{t-1} + \phi_2 f_{t-2} + \cdots + \phi_q f_{t-q} + v_t. \tag{3.4}$$

The law of motion for the idiosyncratic shock $u_{i,t}$ is expressed as an AR(p) process:

$$u_{i,t} = \theta_1 u_{i,t-1} + \theta_2 u_{i,t-2} + \cdots + \theta_p u_{i,t-p} + \xi_{i,t}. \tag{3.5}$$

The disturbances $\xi_{i,t}$ for $i = 1,\dots,N$ and v_t are both i.i.d. normal, with $\xi_{i,t} \sim \mathcal{N}(0, \sigma^2_{i,\xi})$ and $v_t \sim \mathcal{N}(0, \sigma^2_v)$.

[8] "Factor" and "Factor loadings" are technical terms that we use only in the formal model section. In the remainder of the chapter we label them "activity index" and "activity index coefficients", respectively.

Two indeterminacies appear in this setup, which require additional identifying assumptions. First, there is the scale indeterminacy, which can be solved by setting the variance of the factor innovations σ_v^2 equal to a constant.[9] Second, there is the sign indeterminacy of the factor loadings λ_i and the factor f_t. To solve this problem we restrict one of the factor loadings to be positive [Geweke and Zhou, 1996].

The model can be estimated via Gibbs sampling. This procedure enables the researcher to draw from nonstandard distributions, by splitting them up into several standard conditional distributions. In our case, the estimation procedure is subdivided into two blocks: first, the parameters of the model $(\phi_s, \theta_r, \lambda_i, \sigma_{i,\xi}^2)$ for $s = 1, \ldots, q$ and $r = 1, \ldots, p$ are calculated, applying the methods described in Kim and Nelson [1999a]. Second, conditional on the estimated values of the first block, the factor f_t is computed by applying the Kim and Nelson [1999a] approach, using the Carter and Kohn [1994] algorithm. After the estimation of the second block, we start the next iteration step again at the first block, conditioning on the previous iteration step. It can be shown that the conditional posterior distributions converge to the true desired marginal posterior distributions as the number of iteration steps goes to infinity [Geman and Geman, 1984].

Finally, we present our choice of priors. For the factor loadings we used $\mathcal{N}(\overline{\lambda}, \overline{W}_\lambda)$, where $\overline{\lambda} = 0$ and $\overline{W}_\lambda = 100$. For the variance of the innovation of the idiosyncratic components we used an inverted gamma distribution $\mathcal{IG}(\frac{\overline{\tau}_i}{2}, \frac{\overline{\omega}_i}{2})$, where $\overline{\tau}_i = 6$ and $\overline{\omega}_i = 0.001$. Both prior distributions imply that we have hardly any a priori knowledge about the parameter values. For the autoregressive parameters of the factors and the idiosyncratic components we used $\mathcal{N}(\overline{\phi}, \overline{W}_\phi)\mathcal{I}_\phi$ and $\mathcal{N}(\overline{\theta}, \overline{W}_\theta)\mathcal{I}_\theta$, where $\overline{\phi} = 0_{q\times 1}$, $\overline{W}_\phi = \text{diag}(1, \frac{1}{2}, \ldots, \frac{1}{q})$, $\overline{\theta} = 0_{p\times 1}$ and $\overline{W}_\theta = \text{diag}(1, \frac{1}{2}, \ldots, \frac{1}{p})$. Both imply that values for more distant lags are less important. $\mathcal{I}_\phi$ and $\mathcal{I}_\theta$ are indicator functions enforcing stationarity.

3.4 Data

Spree [1978] provides 18 annual time series for the period 1820-1913. The series are very diverse, and include prices, production, productivity, consumption, investment and demographics (Table A.2). The data is aggregated to represent the area of the German Empire as it existed from 1871 on without Alsace-Lorraine if not stated otherwise. The regional coverage of the data in the first half of the 19th century, however, is not as good as in the second half. For the preceding decades many series were often extrapolated backward using regional data; i.e., they represent the whole area in levels, but cyclical variations are likely to represent regional

[9] Among others, Sargent and Sims [1977].

conditions. An overview of the sources can be found in the appendix.

We label this data set "1" and leave it unchanged. Only for the construction of the index of agricultural activity is the agricultural production series substituted by four regional series for wheat and potato production [Helling, 1977].

Spree [1977] also provides a larger data set, consisting of 265 time series for the period 1840-1880. It is an extremely rich data set, comparable in scale maybe only to Hoffmann [1965]. About 50 of the 265 series rely on Hoffmann [1965], 23 on Spiethoff [1955], 22 on Jacobs and Richter [1935], 20 on Borries [1970], 18 on Kirchhain [1973], and 11 on Fremdling [1975]. Additionally, we draw on a large amount of scattered quantitative and qualitative literature, and thus obtain a data set that covers a large proportion of activity in the German economy.[10]

We label this data set "2." It must be reduced due to a number of reasons. Since some single data points are missing, we cannot use the complete data set, as our method needs balanced panels.[11] We also discard a large number of other series, mainly because of redundancies. For example, consumption series can be neglected if imports, exports and production are given for the same commodity. Furthermore, many production series are included both in volumes and in values, of which we use only the volume information. Moreover, we exclude stock market information in order to use stock market indices to check for robustness. We add 18 time series from Spree [1978] that are not part of Data Set 2 in Spree [1977]. The sample we work with finally consists of 93 series (Table A.2, Column 3).

3.5 Research Design

In this section we motivate our research strategy. We start out by comparing how an index of economic activity obtained from a dynamic factor model differs from an output index aggregated by national accounting rules.[12] We then discuss why we use both real and nominal time series. Then we explain our choices regarding the data sets as well as data transformation and filtering. We continue on laying out how we check for representativeness of the data sets. Finally, we show how we separate sectoral subsets and measure to which degree each series is explained by the activity index.

[10]The exact sources for every series can be obtained from the authors or downloaded at `www.histat.gesis.org`.

[11]We experimented with data sets of varying length and breadth, which did not change the results for the business cycle turning points. Figure 3.1 presents an index of economic activity for 1840-80 from 158 series that was only stripped off the redundant series in the data set.

[12]We thank an anonymous referee for suggesting this.

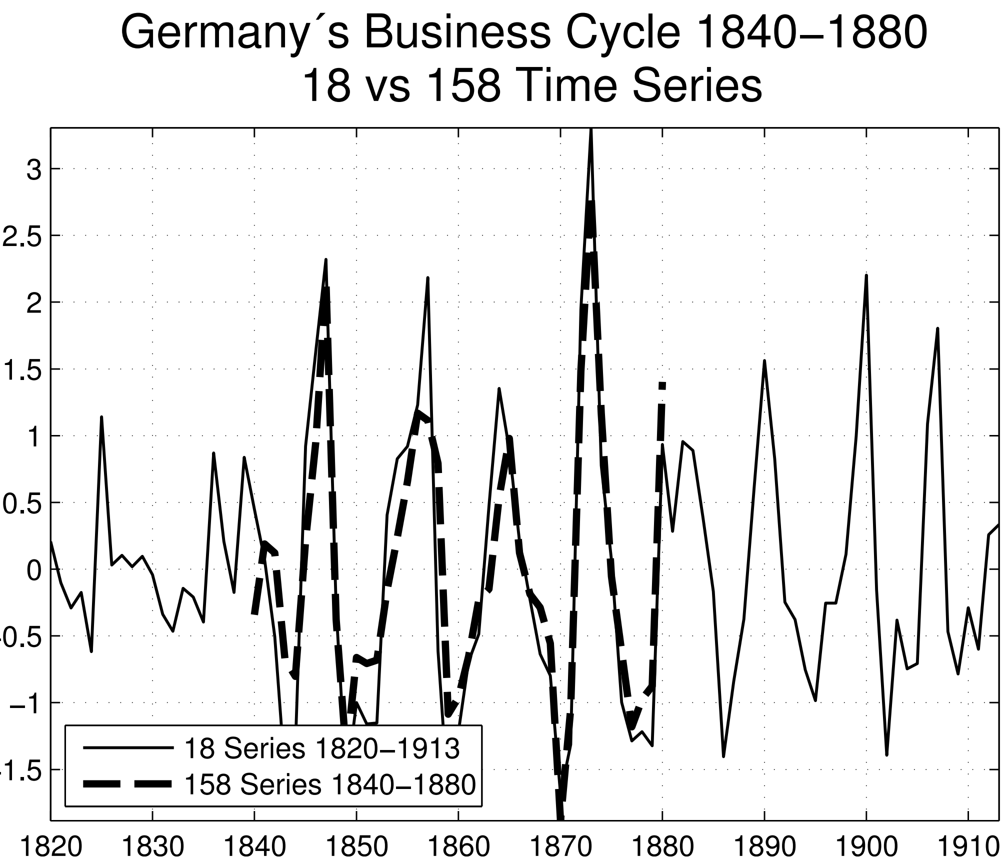


Figure 3.1: Activity index from 158 Series vs activity index from 18 Series. The y-axis depicts percentage deviations from trend.

3.5.1 Comparison of DFM and National Accounting

Dynamic factor models have not been used to replace historical national accounting estimates before.[13] Therefore, we start with a comparison between those two aggregation procedures, using the same disaggregated data set to create an index of economic activity. We have six series of sectoral production between 1850-1913 provided by Hoffmann [1965, p. 451-2]. The series represent manufacturing, mining, agriculture, finance and trade, transport and non-agricultural housing. We also use Hoffmann's aggregate NNP estimate produced from these series.[14] A shortcoming is the small number of series which potentially limits the generality of the results; most of our applications use dozens of input series.

[13]Gerlach and Gerlach-Kristen [2005] may be an exception.

[14]The data can downloaded at `www.histat.gesis.org`. Be aware there is a typo in 1899. It should be 66.6, not 56.6.

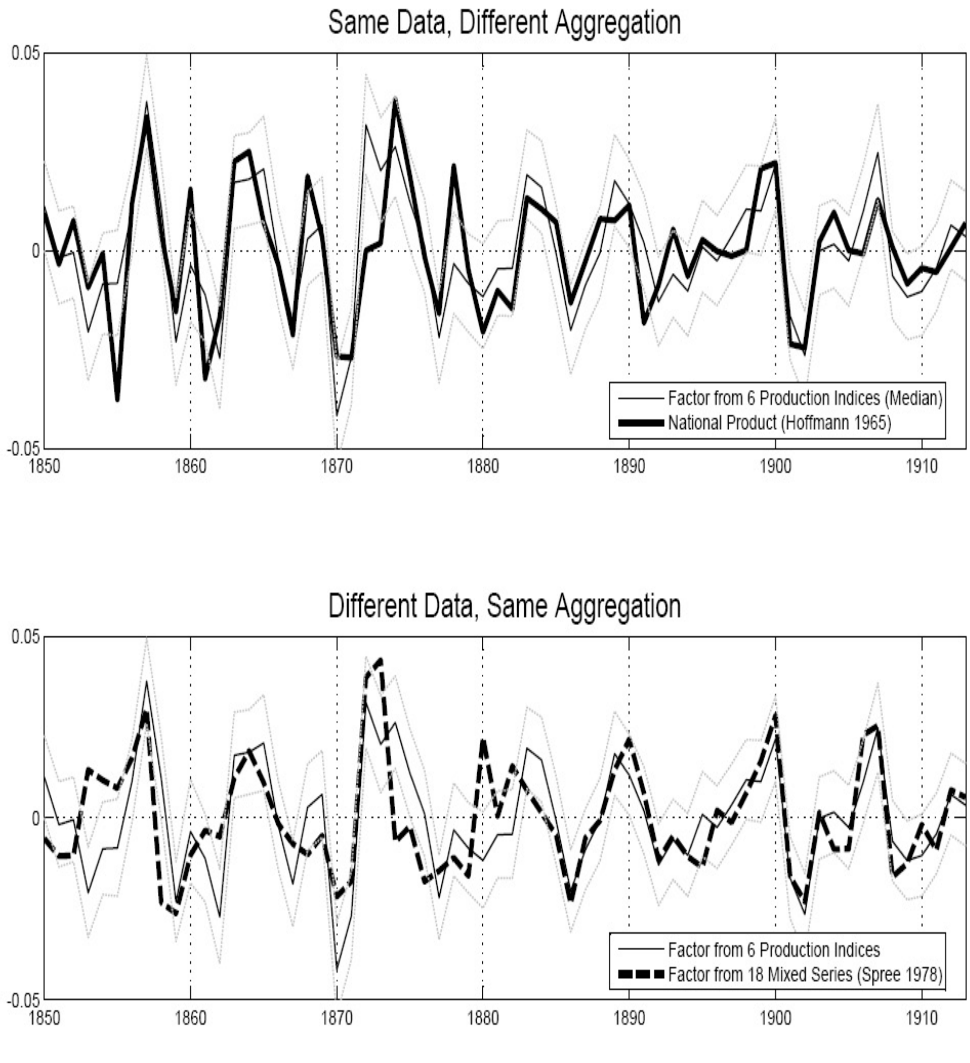


Figure 3.2: Comparison of aggregation procedures. Upper panel: dynamic factor aggregation vs Hoffmann's national product, six series of sectoral production. Lower panel: dynamic factor of Hoffmann's six series of sectoral production vs dynamic factor aggregation of 18 mixed series from Spree [1978].

We find that the dynamic factor model produces an index of economic activity with the same turning points as national product aggregation (Figure 3.2). Only one additional peak in 1878 is produced by Hoffmann's NNP. This shows that the particular strength of DFM is not to extract a "better" representation of cyclical activity when the data is given, but – and this is the argument we want to emphasize most – that it can employ more data. If the data is given, it produces turning points very similar to national accounting.

3.5.2 Real and Nominal Time Series

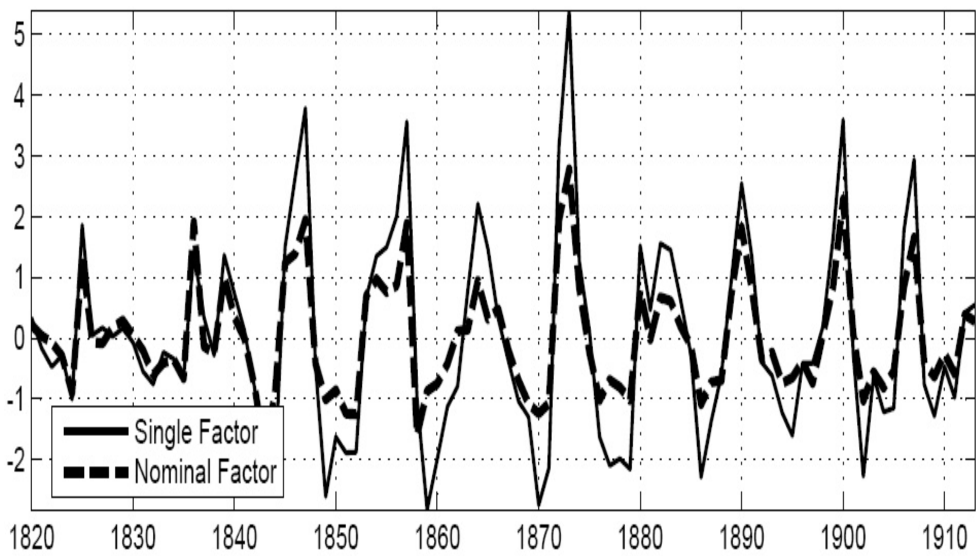
Economists and economic historians are usually interested in real economic activity. For the estimation of our model, however, we use both real and monetary time series. We are aware of potential misinterpretations, but we understand this approach in the tradition of the diffusion index literature as established by Burns and Mitchell [1946]. Looking at the comovement of an indefinite number of time series of unspecified character is a relatively agnostic approach. We do this because real historical time series are often badly measured. Nominal series, however, contain information about the relation of supply and demand that we do not want to discard. This means that in the first step of the analysis, we do not differentiate between real and nominal series.

As robustness checks we set up two alternative models. One is used to estimate an activity index for real and nominal series separately. Doing this, the business cycle dates do not change, as Figure 3.3 shows.

A second alternative is to experiment with a non-structural two-factor model. A non-structural two-factor model is one in which two indices of economic activity are estimated instead of one at a time. It assigns endogenous coefficients to each index (factor) which potentially may represent the real and the nominal side of the economy. In our case it does not identify real and nominal activity indices, however.[15] We conclude from this exercise that in 19th century Germany real and nominal series reflect the same economic shocks, and that the monetary side of the economy does not have its own identifiable cycle.

Just as we do not discriminate between real and nominal series, we neither distinguish between agricultural or industrial time series, public and private sector data, or any other economic structure that could be imposed on the data. Single index or one factor models are known for their strong power in dating business cycles [Stock and Watson, 1998]. Other applications of these models include analysis of the frequency content and of variations in volatility (see for example Del Negro and Otrok [2003], and Ritschl et al. [2007][16]).

[15] Results can be obtained from the authors.
[16] Chapter 4 of this thesis.



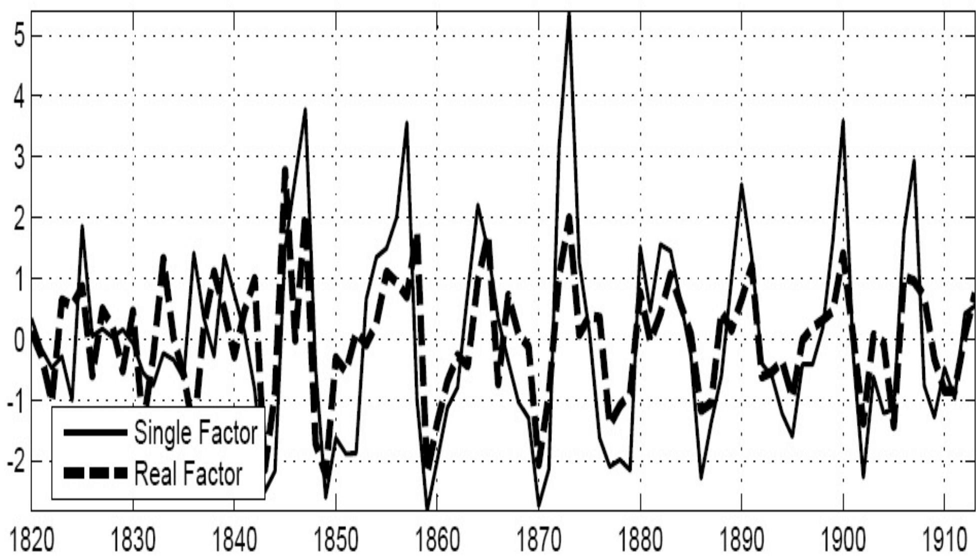


Figure 3.3: Activity index from 7 nominal and 11 real time series, Germany 1820-1913. Index from all 18 series as continuous line.

This clearly differentiates our approach from the business cycle literature that draws on historical national accounts. National accounting proceeds by aggregating data under strong assumptions about their economic structure. For example, sectoral weights are needed to add up output indices from agriculture, industry and service. However, it is often empirically difficult or even impossible to identify the correct weights of the sectors [Hoppit, 1990].

3.5.3 Filtering and Standardization

To eliminate trends, we apply different filters in order to extract the business cycle component from the logarithmized data. The remaining business cycle component is then z-standardized. We employ the Hodrick-Prescott filter with a λ of 6.25 (according to Ravn and Uhlig [2002]) and the more traditional $\lambda = 100$. Alternatively we use the modified Baxter-King filter [Baxter and King, 1999, Woitek, 1998] and the Christiano-Fitzgerald filter [Christiano and Fitzgerald, 2003], which are band pass filters that eliminate cycles shorter than 2 and longer than 15 years. The main results are robust to variations of the filter method.[17] Therefore we report only the Hodrick-Prescott filtered data, which guarantees broad comparability.[18]

3.5.4 Robustness Checks

We propose two robustness checks concerning the choice of series for Data Set 1. We employ the same model to Data Set 2, of which the former constitutes a subset and plot the resulting activity indices against each other. Robustness is shown when both series appear to be similar. Given that the broader set consists of a large number of time series, this would be strong evidence for the relevance of Data Set 1.

A second robustness check was made in order to cover the period after 1880, where Data Set 2 ends. For this we use stock market data. There are good reasons to assume that German stock markets after 1870 were weakly efficient and representative. German stock markets developed vigorously after the Prussian Joint Stock Company Act of 1870 deregulated IPOs. In 1913, market capitalization relative to GDP was 44%, a very high level even at modern standards.[19] Various empirical studies confirm the necessary assumption of weak capital market

[17] As a fourth check we simply take the first differences of the series, still a widely used method in empirical research, but the one that causes the largest distortions in the business cycle component (see for example A'Hearn and Woitek [2001]).

[18] The full set of results can be requested from the authors.

[19] Stock market capitalization fell after World War I, and the 1913-level was only reached again in the 1990s [Rajan and Zingales, 2003].

efficiency [Baltzer and Kling, 2004, Bittner, 2005]. The results are discussed in Section 3.6.

3.5.5 Convergence, Model Parameters, Subsets

Since we are making random draws from a chain of conditional distributions, we have to decide which draws to take in order to make sure that the conditional distributions for the activity index converge to the true desired marginal posterior distributions. From a total number of 30,000 draws for the factor, we delete the first 6,000 to reduce the risk of distorting the estimate through an unsuitable starting point. In order to avoid serial correlation along the Markov chain, we only use every third draw and discard the rest. The remaining 8,000 we finally use for inference. We repeat the estimation using different starting values. This adds a second check aimed at verifying that the results are not sensitive to the choice of the starting values. Second, two subsets of the total set of draws are compared with each other. In all cases, the differences were almost invisible and are therefore not documented here.

As explained in Section 3.3, we can choose the order of the AR-representation of the activity index f_t as well as the idiosyncratic process $u_{i,t}$, i.e. q and p, respectively. We experimented with different orders, and decided on $q = 8$ and $p = 1$. The choice of $q = 8$ reflects that there may be autocorrelation at business cycle frequencies of up to 8 years, while $p = 1$ is chosen for convenience. Alternative orders do not change the results in any relevant way.

We divide Data Set 2 cross-sectionally into subsets to identify the movement of certain sectors: 22 series make up for agriculture, for heavy industries there are 31 series, construction is represented by 5 series, and textile industry by 29 (Table A.2, Columns 4-7).

In order to find arguments about when industrialization occurred, we divide Data Set 1 in shorter pieces to look for variations in time. Data set 2 is divided into cross-sectional subsets and sector-specific activity indices are estimated. At each iteration of the Markov Chain we obtain forecast errors from regressing each single series on the actual draw for the activity index. This tells us how much of each series' variance can be explained by the index and we therefore call R^2. We produce bar graphs that show the R^2s ordered by value. For the interpretation of R^2 in the given context we compare the results only relatively to each other; i.e., we use R^2 as an indicator to see which series is better explained by the activity index than others. No certain value, however, can be assigned that is to be regarded as "sufficient" or "too low", because R^2 is potentially dependent on the number of observables and the relationship is not entirely clear.

3.6 Results

In this section we address the transition of Germany's economy from agriculture to industry, and discuss the case of integration even before 1850. The section concludes with a detailed discussion of our findings on German business cycle history in the light of the literature.

We with the results of the robustness checks. As evident from Figure 3.4, both data sets overlap for the years of 1840-1880. The activity indices obtained from the two sets yield exactly the same business cycle turning points. The comparison to the stock market corroborates this result. Figure 3.4 (lower panel) shows the high degree of correlation between the stock market and the activity index from Data Set 1. It also exhibits that the stock market is leading the activity index. The strong resemblance of the activity index and the stock price index should not be undervalued. The two data sets are independent from each other. Note also that a similar result has been obtained already in a previous study on Germany [Ritschl and Uebele, forthcoming] using frequency-domain techniques.[20] The result is in perfect accordance with what capital market theory would predict, namely that the stock market should be procyclical and leading. To our knowledge, there are few empirical studies about the predictive power of stock prices that confirm the theory so clearly, and even fewer for the 19th century.

The activity index for 1820-1913, estimated from a narrow set of series (Data Set 1), but robust to checks against larger data sets (Data Set 2), is shown in Figure 3.5.[21]

3.6.1 The Transition from Agriculture to Industry

One of the primary features of this chapter is the use of the dynamic factor model to investigate structural transition. We do this by restricting the sample either in time, or across series, or both. We look at the activity index itself, the activity index coefficients and at the $R^2 s$, the explanatory power of the activity index for each series. First, we discuss the sectoral results from splitting up Data Set 2 for 1840-1880. We then look into the longitudinal subsets taken from Data Set 1.

93 series, 1840-1880

The activity index from the total set is represented as the heavy broken line in Figure 3.4 (upper panel). From Data Set 2 we construct a subset for the agri-

[20] See Chapter 2.

[21] The scale of the activity index in Figure 3.5 is not interpretable as explained in Section 3.3. In Figures A.2 and A.1, however, the activity index is calibrated to the standard deviation of Burhop and Wolff's (2005) "Compromise" NNP estimate for comparison purposes.

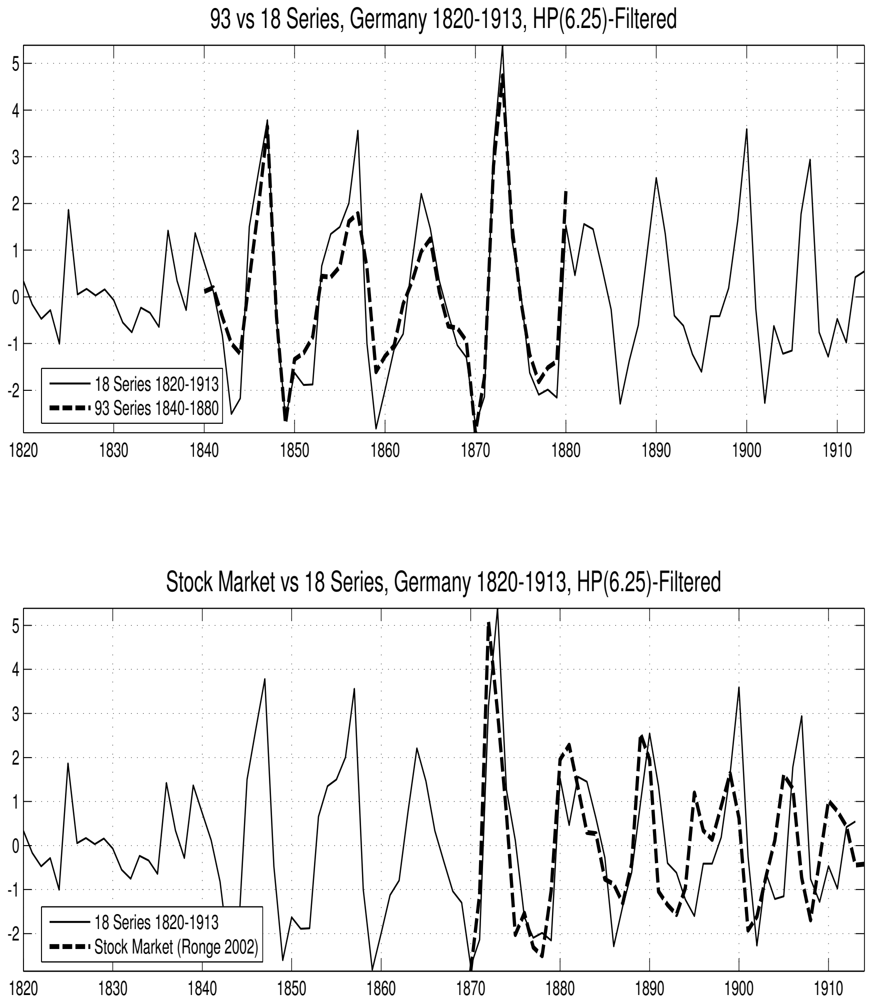


Figure 3.4: Activity index from 18 time series vs 93 series (upper panel), Germany 1820-1913, and stock market index (lower panel, Ronge 2002), Germany 1870-1913.

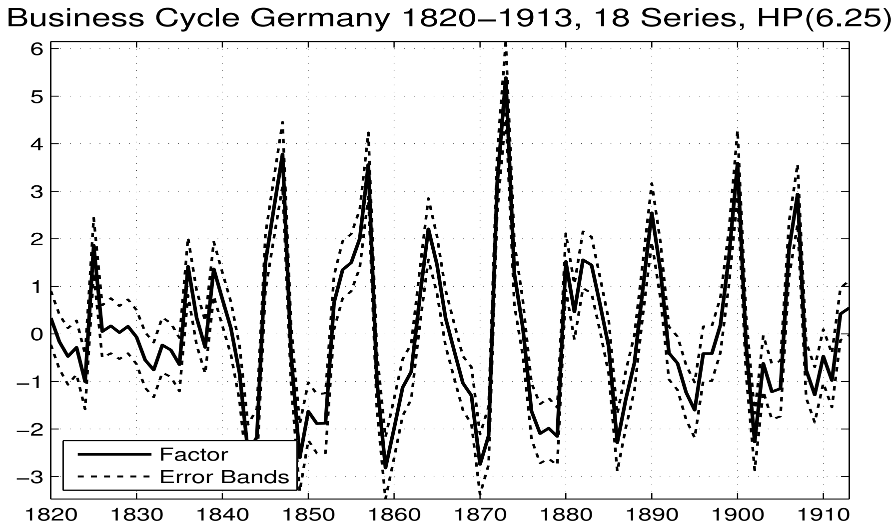


Figure 3.5: Activity index from 18 time series, Germany 1820-1913.

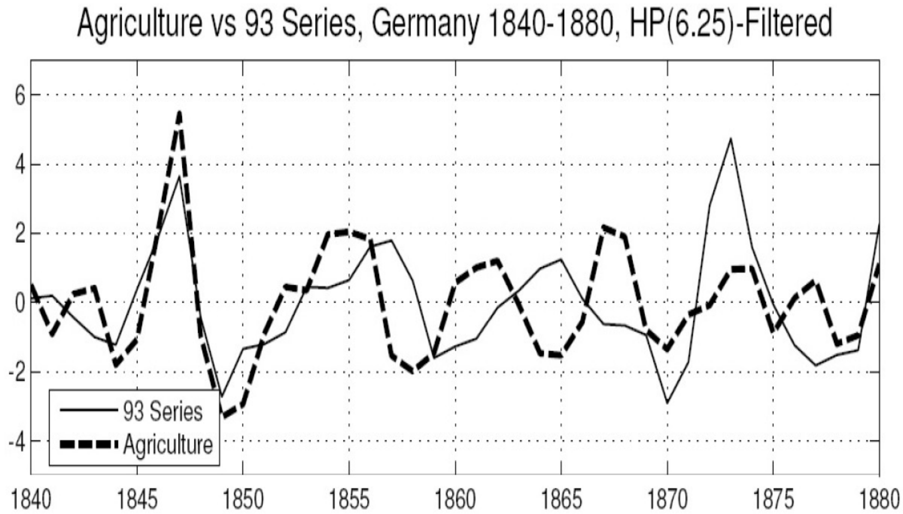


Figure 3.6: Activity index from 93 time series vs sector-specific activity index for agriculture, Germany 1840-1880.

cultural sector that includes an index of net crop production, various price series and some agricultural trade figures. Figure 3.6 shows the index for agricultural sector-specific activity.

It features a very dominant peak in 1847 and less prominent ones in 1855,

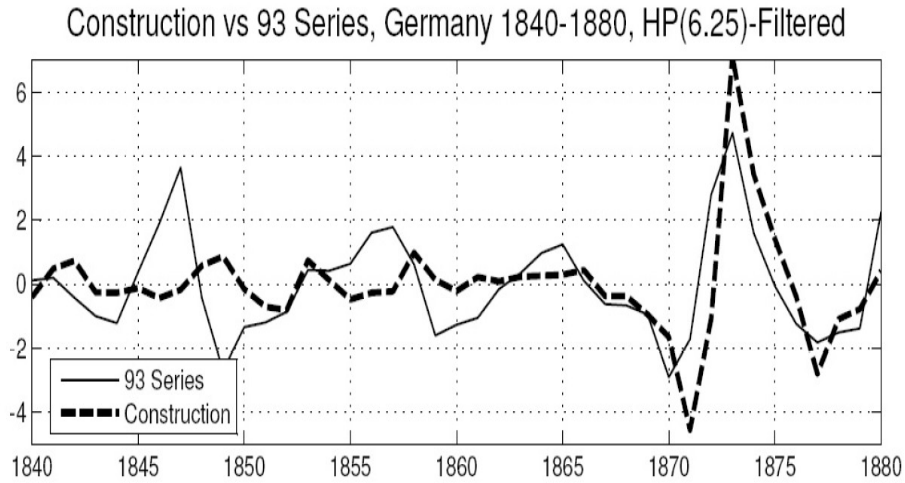


Figure 3.7: Activity index from 93 time series vs sector-specific activity index for construction, Germany 1840-1880.

1862 and 1868 as well as two smaller peaks in 1873 and 1876. The peak in 1847 is both due to a massive increase in grain prices and production increases. The price peaks were not only observed in Germany, but all over Europe, the last European crisis of the type "ancienne" [Le Roy Ladurie, 1974]. Berger and Spoerer [2001, p. 303] report that due to crop failures in preceding years another bad harvest was expected but in fact Prussian grain production grew by about 120% compared to 1846 [Helling, 1977, p. 227], which is reflected in the index of net crop production. Some authors however, do not recognize this surge in agricultural production. Borchardt [1976, p. 258] for example mentions solely the "catastrophical crop failure" and the "undescribable misery" of the years 1846 and 1847, but not the production increase, perhaps because prices did not fall. The unresponsiveness of agricultural prices allegedly was caused by the world market, where expectations were influenced by past harvest failures [Bergmann, 1979, Berger and Spoerer, 2001]. Since both prices and production had a cyclical peak, 1847 was surely a very good year for agricultural producers in Prussia and similar in Bavaria, Saxony and Württemberg [Helling, 1977, p. 229].

Consumers, however, had to bear the burden of the high prices dictated by world markets and previous bad harvests. According to Berger and Spoerer [2001, p. 303], this caused a severe downward pressure on real wages and spilled over to the industrial sector in 1848. Because a major share of real wages was squeezed too close or even below subsistence level, the consumption of manufactured goods declined. According to Berger and Spoerer [2001, p. 305], investment suffered from rising interest rates as credit demand increased. Thus, 1847 – the "good year" in terms of our activity index – was a considerably bad year for at least industrial workers and may have caused the subsequent economic downturn.

The literature supports that Germany up to mid-century was still a largely agricultural economy [Borchardt, 1976, p. 258]. In our framework this is reflected in comovement of the sector-specific activity index for agriculture with the overall activity index (Figure 3.6). However, this changed quickly in the following decades. Already in the 1860s the upturn shown by the overall activity index is matched by a downturn of the agricultural activity index. Thus, as opposed to 20 years earlier, there is no evidence anymore of a spill-over from agriculture to industry. A decoupling of agricultural and industrial cycles seems to have set in the 1860s at the latest. The existing scholarly opinions do not explicitly address the question of shock transmission from the agricultural to the industrial sector. However, their interpretation, mainly based on historical national accounts, suggests a later transition to an economic regime that fluctuates mainly in accordance with industrial cycles and less with harvest luck. For example, until 1890 agriculture remains the sector that contributes more to national income than any other single sector, a year when it employs 42% of the workforce [Hoffmann, 1965, p. 33 and 35]. Borchardt [1976, p. 255 and 259] speaks of an economy in transition before 1870 and attributes the beginning to the 1840s, but acknowledges "strong influences of agricultural cycles on the economic aggregates in the 1850s and 1860s". Similarly, Spree [1978, p. 101] explains the upturn until 1847 partly as driven by industry, and the "Gründerzeit"-boom 1873 entirely as a "modern" cycle. Comparing our agricultural sector-specific activity index with the overall activity index, however, we shift the completion of the transition by a decade backwards: the boom shown by our activity index in the 1860s was already independent of agriculture.

18 series, 1820-1913

We now turn to the investigation of Data Set 1. It consists of 18 time series from various sectors, whereas above we reviewed more time series covering a shorter period. The evidence stems from observing the activity index coefficients assigned to the individual series. The coefficients are found by statistical criteria. Each represents one data series, and can be understood as a measure of the relative importance an individual series has in the activity index.

Five out of 18 series receive very high coefficients relative to the other ones (Figure 3.8): raw materials' wholesale prices, Prussian iron and coal production, Scottish import prices for iron, and Berlin and Hamburg discount rates. The picture clears up even more if we look at R^2, the share of variance explained by the activity index (Figure 3.9). While 30% to 70% of the variances of these five series

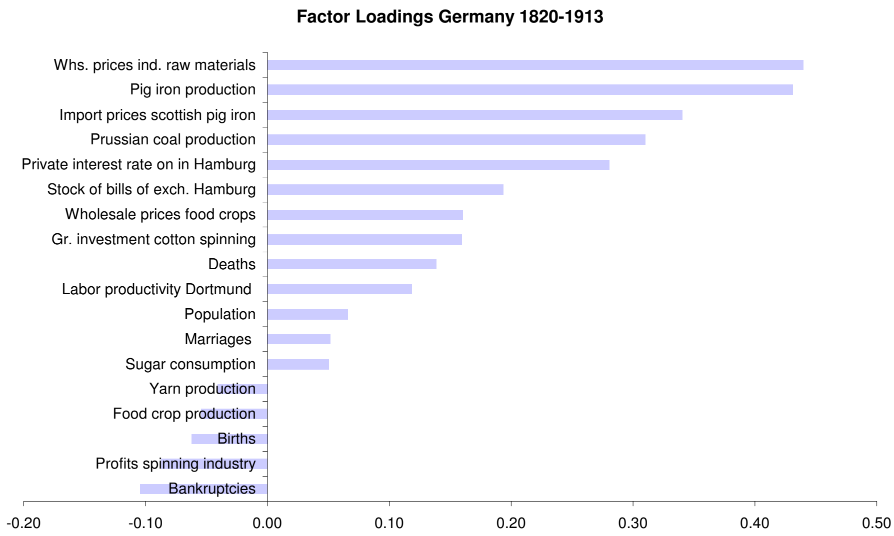


Figure 3.8: Activity index coefficients from 18 time series, Germany 1820-1913.

are explained, none of the other series' variance is explained by more than 13%. This reveals an overwhelming emphasis of the model on the industrial sector and investment demand.[22]

We now look at certain subperiods of the 19th century, extending the data from earlier to later periods. First we compare the R^2s for 1820-50 of to a subset for the years 1820-1880. Among the 1820-50 series, we notice comovement across sectors (Figure 3.10) as expressed in the relatively high R^2 for many series. Eight out of 18 series have 20% percent of their variance explained by the activity index, five of them are not heavy industry series.

Adding information about the next 30 years changes the picture considerably: now four series are explained well by the activity index (at a 20% threshold) and all of them represent heavy industries (Figure 3.11). In contrast, including the time until World War I does not change the explanatory power nor the activity index coefficients in any meaningful way anymore (Figure 3.9).

In summary, both the cross-sectional and the inter-period comparison tell the same story: a strong positive correlation between agriculture and the overall econ-

[22]The appendix provides a table with all coefficients and R^2s.

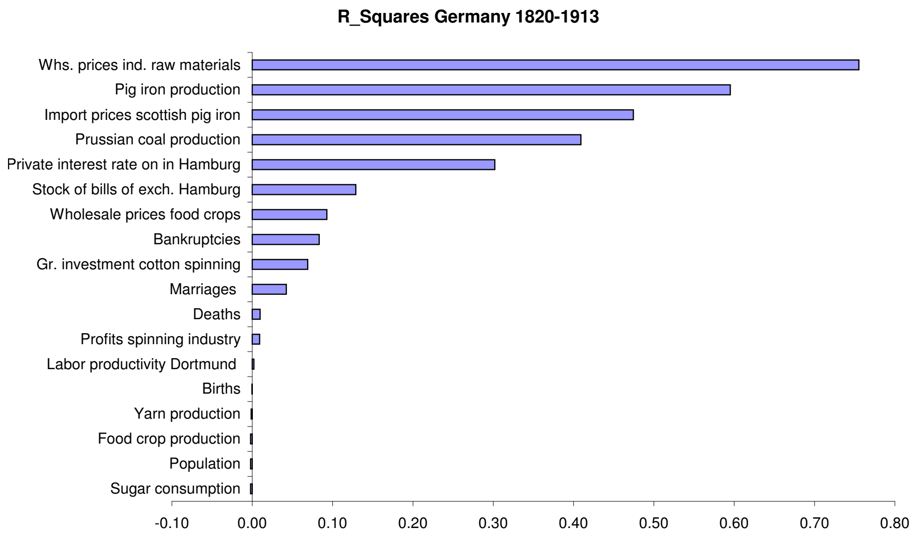


Figure 3.9: R^2 from 18 time series, Germany 1820-1913.

omy up to mid-century, then decreasing, while heavy industry – playing already a role before 1850 – becomes dominant not later than 1880.

3.6.2 Integration of the German Economy before 1850

Figure 3.5 shows the activity index calculated from Data Set 1. It features an upturn in 1825 and a double peak in 1836 and 1839. A subset is formed that isolates the data between 1820 and 1850. Here we split up the index of agricultural production into its main regional components for Prussia, Saxony, Württemberg and Bavaria to allow for potential geographical variation (data from Helling [1977]). Interestingly, in Figure 3.10 we observe comovement in terms of R^2 across regional series (e.g. Hamburg/Berlin interest rate, Prussian pig iron, Bavarian crops), which also comove with supraregional aggregates (population, cotton investment, wholesale prices raw materials). The inter-regional comovement indicates that economic integration was already under way.

Germany's political landscape until 1871 was scattered and the impact of railway transport started only in the mid-1830s; certainly after we find a common business cycle. Our finding therefore could be regarded as quite interesting. It

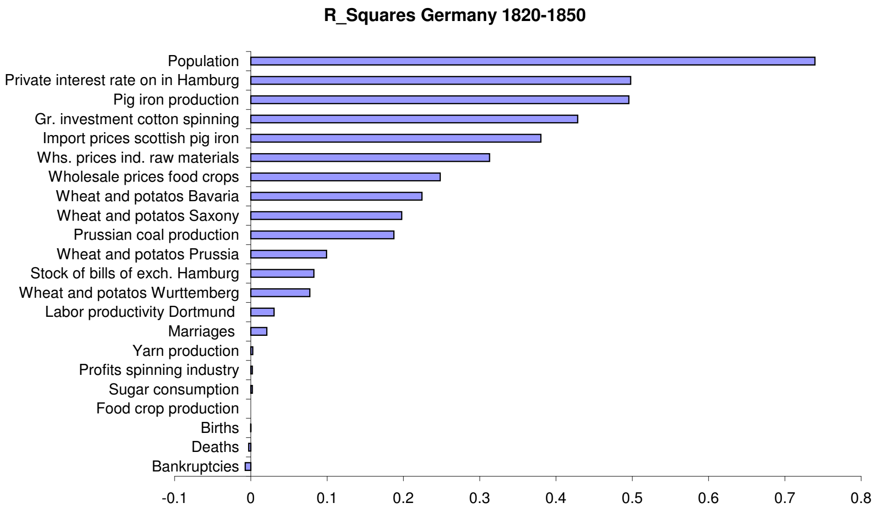


Figure 3.10: R^2 from 18 time series, Germany 1820-1850.

could be argued, however, that the Zollverein had an economically integrating effect and therefore a common business cycle before 1850 should not be surprising. In contrast to this argument Craig and Fisher [2000, p. 212] regard the Zollverein and the railroad as generally overrated in the discussion of German 19th century economic integration. They suggest that political integration, the Zollverein, and the railroad were not the cause, but rather the consequence of economic integration and growth. In accordance with this argument Kaufhold [1993, p. 577] reports that railroads were publicly discussed early in the 1820s in Germany. Bairoch [1982] accordingly reports substantial growth rates for Germany between 1800 and 1830. Another argument follows from Berger and Spoerer [2001], who compare the integration of Prussian and European grain markets. Drawing on Fremdling and Hohorst [1979] they take the Prussian coefficient of variation starting in 1820 as a benchmark level for grain market integration and observe that the European markets converge to that level by the early 1840s [Berger and Spoerer, 2001, p. 300].

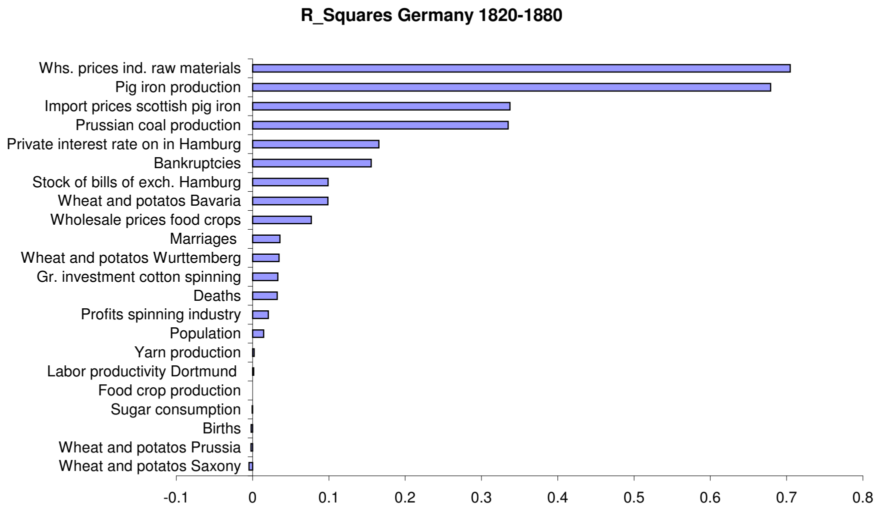


Figure 3.11: R^2 from 18 time series, Germany 1820-1880.

3.6.3 Business Cycle Chronology in Light of the Literature

Figure 3.5 shows the activity index calculated from Data Set 1. Note that the cyclical swings occur very regularly over the whole period. The average cycle duration was 8.5 years with a standard deviation of 1.25 years. An overview of the business cycle chronologies can be found in Table 3.1.

The 1840s We confirm most of the frequently mentioned economic swings in 19th century Germany: the activity index features the downturn in 1848 that could be felt throughout the continent and was accompanied by political turmoil in many European countries. The literature supports the downturn with no exceptions, but offers varying explanations: Kaufhold [1993, p. 577] emphasizes a deceleration in railroad investment after the first railroad boom in the 1830s and -40s. Meanwhile, Berger and Spoerer [2001] relate the revolutions and the economic downturn to bad harvests in the preceding years. Their argument and the relation between industry and agriculture will be addressed in greater detail further below.

The 1850s Borchardt [1976, p. 260] reports an upswing in the early 1850s, with an upper turning point in 1857. Our activity index confirms this. According to Spree [1977, p. 343], strong investment in heavy industry was a major contrib-

Table 3.1: Comparison of business cycle dating for Germany, 1820-1913.

	Activity Index		Burns&M. (1946)		Spieth. (1955)		B.&W. (2005)	
	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak
1	–	1825	–	–	–	–	–	–
2	–	1836	–	–	–	–	–	–
3	1843	1847	–	–	–	–	–	–
4	1851	1857	–	–	–	–	1855	1859
5	1859	1864	1866	–	–	–	1862	1864
6	1870	1873	1870	1872	–	1872-73	1871	1874
7	1879	1882	1878	1882	1878-79	1881-82	1880	1878
8	1886	1890	1886	1890	1883-84	1889-90	1891	1889
9	1895	1900	1894	1900	1893-94	1899-00	1894	1898
10	1902	–	1902	1903	1901-02	–	1902	1905
11	–	1907	1904	1907	–	1906-07	–	–
12	1911	–	1908	1913	1908-09	1912-13	1910	1908

Spiethoff's dating procedure adapted for comparison: peaks between slumps and booms, troughs between booms and slumps.
Compromise from Burhop and Wolff [2005]. They also report troughs in 1873, 1877, 1886/87, 1906, and peaks in 1884, 1893, and 1913, but with lower intensity.

utor to this boom, but then credit shortages occurred after banking panics in the U.S. and stock market crashes shook investors' confidence. Thus, the downturn after the peak in 1857 was not a uniquely German experience, but was felt worldwide. Still, neither in scale nor in scope was it comparable to the Great Depression after 1929 [Borchardt, 1976, p. 261].

The 1860s Departing from most of the literature, we obtain a clear boom in 1864, a period that is commonly seen as mainly characterized by Prussia's wars in 1864 and 1866. Interestingly, the textile industry has a strong peak in 1864, suggesting the possibility of a causal relationship (Figure 3.12). One aspect of the peak in our activity index may be high cotton prices that can most likely be traced back to the production decline in the war-torn United States [Spree, 1977, p. 346], a fact that may explain the notion of a rather "peculiar" textile industry cycle [Borchardt, 1976, p. 262].

Spree [1977, p. 347] reports positive growth rates in heavy industry in the early 1860s. This means he disregards the widespread opinion of a lower turning point in 1866 as reported for example in Borchardt [1976, p. 262]. Borchardt's view of a crisis around 1866 assumes a subsequent upturn starting not later than 1869. In contrast, our activity index peaks in 1864 and then experiences a steady downturn until 1870, when it finally starts to grow again. This strongly confirms Spree's (1977) tacit revision of the traditional view on the 1860s' business cycle. Our result partially confirms Burhop and Wolff [2005] who find the 1864 boom, but also a bust in 1867, which we cannot find.[23]

The 1870s Our activity index peak in 1873 corresponds to the *Gründerzeit* startup boom after the foundation of the Empire of 1871 and the victory over

[23] See the appendix for a comparison of our index and the "Compromise"-NNP estimate.

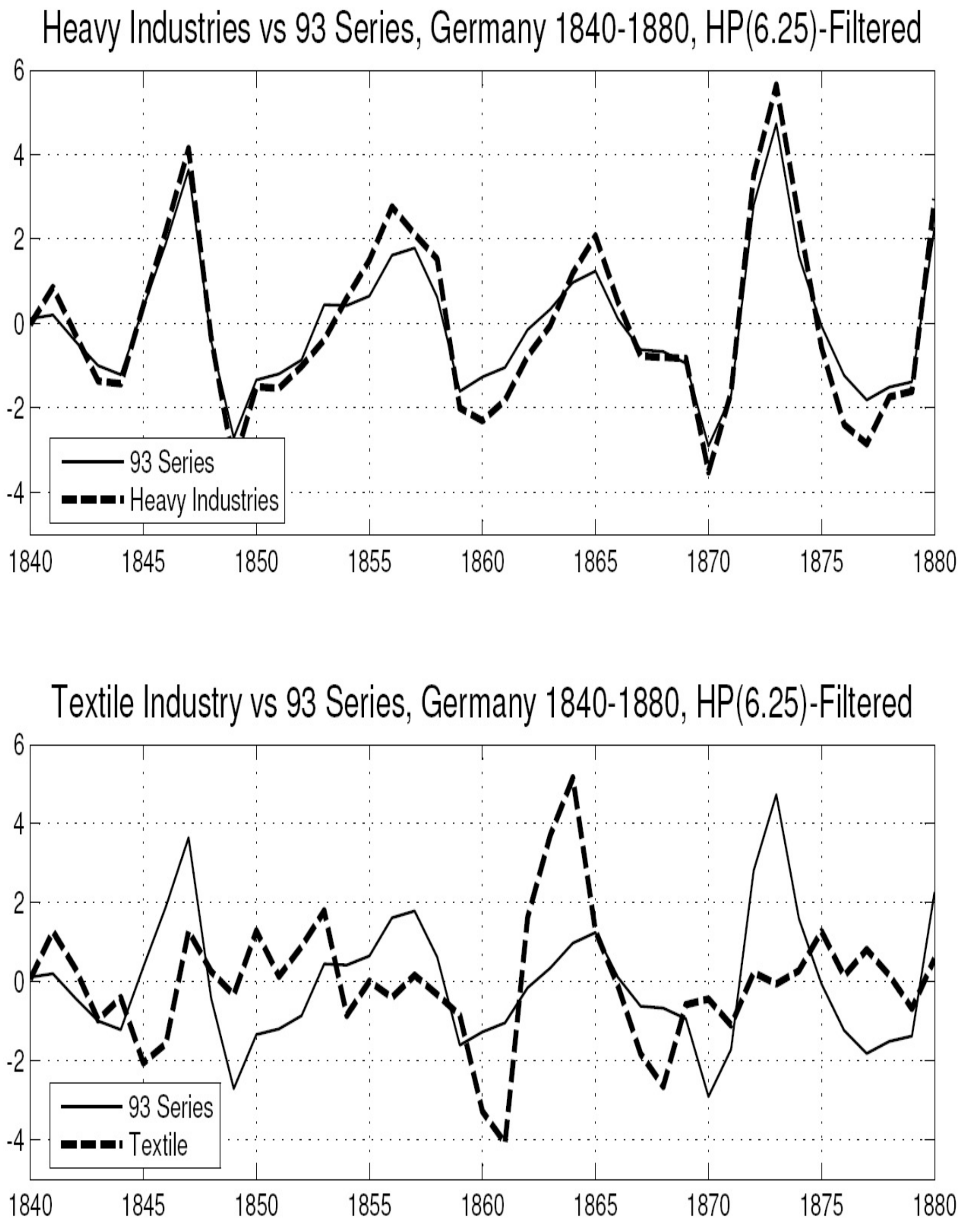


Figure 3.12: Activity index from 93 time series vs sector-specific activity indices for heavy industries and textile industry, Germany 1840-80.

France. The subsequent steep decline, also shown by the activity index, is known as the *Gründerkrise*, or startup bust. To our knowledge, with the exception of Burhop and Wolff [2005], neither the contemporary nor the recent literature has generally questioned the existence of this boom-bust pattern. Borchardt [1976, p. 205], drawing on Hoffmann's (1965) "Expenditure" NNP estimate, acknowledges "above average growth in the years 1870-74 and stagnation up to 1880 (Figure A.1). He also reports pig iron consumption, a traditional investment indicator, to have increased between 1868 and 1873 by 140% (p. 262). The literature also generally agrees on the subsequent period of depression. Fischer [1985, p. 392], using Hoffmann's (1965) "Output" NNP estimate, calls it a "severe recession", while Borchardt [1976, p. 265] emphasizes its unusual duration and its "unparalleled" increase in unemployment (Figure A.2).

The doubts about this business cycle pattern were expressed by Burhop and Wolff [2005]. As Ritschl and Uebele [forthcoming] point out, their findings can be explained by the deflation procedure.[24] Burhop and Wolff's (2005) estimate is a weighted average of four real NNP series they take from Hoffmann [1965] and Hoffmann and Müller [1959]. Their nominal NNP estimates show a different cyclical behavior than the deflated series due to the cyclical information contained in the price index. This effect is particularly strong with the series by Hoffmann and Müller [1959], since nominally it is very smooth, and thus the fluctuations of the price index translate almost unchanged into the deflated series. This causes a downturn in the early 1870s in Burhop and Wolff's (2005) averaged NNP-measure, because Hoffmann and Müller's (1959) series has a 50% weight in it (Figure A.1, "Taxes").

Burhop [2005] revised Hoffmann's (1965) industrial production figures for pre-WWI Germany. He confirms the boom of the early 1870s, but finds it was limited and mainly driven by construction. Our activity index from the construction subset indeed has a pronounced peak in 1873, and thus confirms Burhop's (2005) findings (Figure 3.7). Still, other sectors were involved in the upswing as well. The sector-specific activity index calculated from a subset for heavy industries peaks as well in 1873 (Figure 3.12).

The 1880s During the 1880s we identify a recession with a lower turning point in 1886. This trough is also reported by Borchardt [1976, p. 267] on the basis of Hoffmann's (1965) "Output" national expenditure estimate (Figure A.2). Burns and Mitchell [1946, p. 79] had already posited the existence of a slump in that year using disaggregated quarterly and monthly series. Burhop and Wolff [2005] also find a minor recession in 1886 (Figure A.2).

The 1890s The subsequent 1890 upper turning point and the 1894 downturn of our activity index can also be found in Burns and Mitchell [1946, p. 79], and

[24] Chapter 2 of this thesis.

Spiethoff [1955, p. 123f]. Borchardt [1976, p. 267] identifies investment (especially housing investment) as one of the driving forces for this upturn. Burhop and Wolff [2005] as well as Craig and Fisher [1992] find a trough in 1894 as we do, but also an additional one in 1891 (Figure A.2).

1900-1913 Based on the analysis of 171 monthly time series Grabas [1992] confirms the upper turning points of the activity index in 1900 and 1907/8. Grabas and Burns and Mitchell [1946, p. 78f] use monthly data and report an upturn for Germany, France, Britain and the U.S. for early 1907 and an immediate downturn late in 1908. Borchardt [1976, p. 269], based on NNP estimates, describes an upturn starting in 1903 until 1906/7, then transforming quickly into a crisis with the upturn following 1909/10.

We find the same peak as Grabas (1992) and Borchardt (1976) in 1907, but a lower turning point as late as 1911, before the business climate eases again. Thus, while there is agreement on the peak in 1907 and the downturn in 1911, we have no evidence for a short-lived cycle in between.

3.7 Conclusion

In this chapter, we have made an attempt to identify the German business cycle of the 19th century. Our approach relies on the pioneering work of Burns and Mitchell [1946] and recent developments in dynamic factor analysis. This method allows us to avoid the use of aggregate data and to replace it with statistical aggregation from a large number of disaggregate historical times series. This helps us to relax the data constraints facing historical business cycle research. Since national accounting needs a predefined set of macroeconomic data, it cannot use many of the historical data series that exist. Instead, it must fill gaps by approximations that have the potential to contaminate the other, well-measured data. In contrast, factor analysis allows us to exploit the information content in a large number of existing historical time series, irrespective of whether they would sum up into meaningful national account aggregates. As an analytical tool we add the comparison of sector-specific economic activity to investigate sectoral transition and market integration. Surprisingly, strong confirmation for the method comes from a comparison to the financial sector: a blue chip stock market index exhibits high correlation with our activity index, and leads it by about one year.

Our sectoral results suggest that industrialization influenced the German business cycle earlier than national accounts have suggested so far. Before 1850, all major sectors contributed evenly to the business cycle. Extending the analysis to the 1880s, we find that the business cycle was mainly driven by the industrial sector. Notably, agriculture began to move counter-cyclically in the 1860s. We believe that this confirms Spree's [1978, 1977] notion of a common German business cycle that was influenced by industry already in the 1840s and clearly dominated by industry around 1880. We also find evidence for a common cycle that potentially reaches back to the 1820s, a confirmation of the notion of an early common cycle featured in the convergence literature à la Craig and Fisher [2000].

For the period after the foundation of the Empire of 1871, we mostly confirm the traditional NBER chronology by Burns and Mitchell [1946]. Notably, we find strong evidence in favor of the "Gründerzeit" or startup boom in Germany after 1871, which had been called into question by Burhop and Wolff [2005]. However, we find little support for the shorter and less regular cyclical pattern suggested by the national account estimates of Hoffmann [1965].

The methods employed in this chapter have a natural application to other industrializing economies where historical national account data is poor. Using factor analysis seems to us a promising alley of historical and applied business cycle research, and a useful complement to historical national accounting.

Chapter 4

The U.S. Business Cycle 1867-1995: Dynamic Factor Models vs National Accounts

4.1 Introduction

Measuring the American business cycle in the long term has been the subject of much debate. While there is broad agreement on the business cycle turning points, the issue of volatility is still not fully resolved, as different available estimates yield contradictory results. How severe were the key recessions other than the Great Depression of the 1930s; that is, the recessions of the mid-1880s, of 1907, and of 1920/21? Was wartime prosperity in the mid-1940s really so strong? And has the U.S. business cycle become more moderate since World War II, not only with respect to the interwar period but also compared to the prewar years?

Researchers have disagreed on the severity of the downturn after World War I as well as on the other two questions. Following Burns [1960], DeLong and Summers [1986] argued that business fluctuations after World War II were more moderate than before World War I, and certainly milder than during the interwar period. This view was challenged in a series of papers by Romer [1988, 1989], who argued that postwar stabilization relative to the decades before World War I was an artifact of the historical output and unemployment data.

Given the lack of reliable aggregate series for the decades before 1929 when the official National Income and Product Accounts (NIPA) set in, existing evidence was based on Historical National Account (HNA) estimates. Most of the debate evolved around two such rivaling series and their implications for U.S. business cycle volatility since the 19th century. Balke and Gordon [1986, 1989] modified a popular GNP series originating from the Commerce Department, for which they produced a widely used quarterly interpolation. The high volatility of this series before World War I, as compared to the rather moderate fluctuations of postwar GNP, shaped conventional wisdom in the 1980s. Romer's challenge to this view was based on a revision of the alternative series of Kendrick [1961], which she argued was less prone to spurious volatility.[1] Her results implied that there was no postwar moderation relative to the pre-World War I years. However, her own calculations have been criticized for depending on assumptions which are not empirically testable given the lack of historical GNP data, see Lebergott [1986]. Following Kim and Nelson [1999b], McConnell and Perez-Quiros [2000], Blanchard and Simon [2001], and Stock and Watson [2002], research on the stabilization of the U.S. business cycle has therefore focused mostly on moderation within the postwar period itself.

The present chapter offers an alternative but complementary approach to measuring the volatility of the U.S. business cycle in the long term. We draw on the growing literature on diffusion indices (using a term of Stock and Watson [1998]), which are distilled from a large panel of disaggregate time series using dynamic factor analysis (DFA). Stock and Watson [1991] developed an unobserved component model for disaggregate series representing the U.S. postwar economy which reliably replicates the NBER's business cycle turning points.[2]

Factor models have become popular as an alternative to national accounts because they aggregate a large amount of disaggregate information and are less affected by data revisions than national accounts. Disaggregate series are often abundant for historical periods, but usually do not match national accounting categories well, or the information needed for proper aggregation is incomplete. As a consequence, proxies must be used, which can be controversial. The DFA approach replaces the questionable aggregation techniques used in the construction of HNAs with a statistical aggregator. Series that would be of limited use in reconstructing HNAs can now be exploited for their business cycle indicator characteristics, i.e., their contribution to the common component.

Romer [1991], along the lines of these arguments, undertook an investigation of disaggregate commodity output series for the U.S., comparing their univariate time series characteristics between 1889-1914 and 1947-1984. She also estimated a simplified version of the dynamic factor model we use, however on a narrower and shorter data base. Her principal findings are very similar to ours. Other notable applications of DFM were alternative measures to HNA estimates. Gerlach and Gerlach-Kristen [2005] presented one for Switzerland between the 1880s and the Great Depression. Sarferaz and Uebele [2007] employ a Bayesian dynamic

[1] Both the Commerce and the Kendrick series are related to earlier work by Kuznets [1941, 1946], see Romer [1988] for a discussion.

[2] Stock and Watson [1998] analyzed 170 series successfully forecasting U.S. postwar CPI and IP.

factor model to obtain an index of economic activity for 19th century Germany, comparing it to different rivaling HNA-based chronologies.[3] The present chapter extends this methodology to the historical application of macroeconomic diffusion indices where the aggregation coefficients or factor loadings may change over time. Application of time-varying factor loadings allows to capture structural change, which is important over a time span of more than 100 years, and which would be suppressed if the econometric setup assumes constant parameters.

Our chapter studies two main aspects of U.S. business cycle volatility since the Civil War. One is the volatility increase over World War I, which was pronounced according to Balke and Gordon [1989], or only marginal, as claimed by Romer [1988]. Second, a comparison between the post-World War II era and the period before World War I; a reflection of the discussion between Balke and Gordon [1989] and Romer [1989]. We also comment on the boom associated with World War II, a discussion started in Kuznets [1945] and summarized in Higgs [1992].

The disaggregate data in the present chapter are taken mostly from the Historical Statistics of the U.S., see Carter et al. [2006]. One is from NBER's Macrohistory Database, which itself dates back to the business cycle project of Burns and Mitchell [1946]. Drawing on these standard sources, we obtain a panel of 53 consistent series from 1867 to 1995. Evidently, the use of consistent data over such a long time span generates potential problems of obsolescence. However, we find that in spite of these potential limitations, the factor models we construct on the basis of our data track the official postwar data on GNP and price levels quite well.[4]

A key element of our empirical strategy involves dealing with structural change by allowing the model parameters to vary over time. This helps to address what Romer [1988] identified as a critical weakness in the construction of HNA, the need to impose constant aggregation weights over long time periods. We find that allowing for even small degrees of structural change leads to an unambiguous rejection of the postwar moderation hypothesis. Balke and Gordon [1989] and Romer [1989] disagreed on whether there was a substantial or no decline in postwar volatility relative to the period before World War I. Both assumed constant parameters but differed in their methods of applying national accounting procedures. While we are able to reproduce their results with a fixed coefficient model, the model with time-varying coefficients suggests that the issue is not whether there was a postwar moderation relative to the 19th century but rather how large the volatility *increase* was. That said, our method effortlessly replicates the standard evidence for business cycle moderation within the postwar period. This in-

[3] See Chapter 3 of thesis.

[4] We have also constructed a wider set of 98 comparable series for the subperiod from 1867 to 1939 to capture the critical volatility increase over World War I. The principal results, available upon request, are the same.

cludes the moderation after the early 1980s, although this effect is somewhat less pronounced than in the NIPA data on GNP.

Time variability of the model parameters plays a less pronounced role in determining the volatility increase over World War I. We find that aggregate volatility changed more than both Romer [1988, 1989] and Balke and Gordon [1989] asserted, with little difference between the time varying and the constant parameter model.

Our factor model mostly replicates existing chronologies of business cycle turning points. An exception is World War II, where the factor misses the strong and long lasting wartime boom, followed by a deep recession, that is evident in the NIPA data. Our results resemble much more Kuznets' alternative estimate which accounts for military expenditure differently and therefore seems to yield a more accurate picture of net value added by the government sector.

We also introduce identifying restrictions to distinguish between real and nominal factors, as well as between various sectors, notably agriculture and the rest of the economy. We find that none of our main findings are affected by these robustness tests, but obtain a second important result for the comparison between aggregate volatility before and after the World Wars. As we allow the structural parameters to change, the postwar period exhibits more nominal stability than the prewar era. This finding does not confirm the results of Balke and Gordon [1989] who concluded that real output persistence increased but nominal stabilization did not occur after World War II. With constant aggregation weights we can reproduce this result, while allowing the weights to change over time reverses the conclusion. At the same time, we find that the nominal factor obtained with time varying parameters captures movements in the CPI very well, and indeed is a good forecast for the latter at a one-year lead.

Furthermore, this result touches upon the discussion about the relationship between postwar and prewar real and nominal volatility. Allen [1992] describes the nominal wage counterpart to Romer's [1986b] paper about spurious unemployment data. Our results are in line with his, and may lead to an explanation of the observed relative volatility pattern between the 19th century and the postwar period.

Time variability of the model parameters again plays less of a role in replicating the standard evidence on reduced nominal volatility after the 1980s (see e.g. Cogley and Sargent [2005], Primiceri [2005]). We find this effect for all relevant subsets of our dataset, as well as with both constant and time-varying parameters.

The next section provides a non-technical motivation of our approach. Section 4.3 expounds the model and the priors. Section 4.4 discusses the data and the strategies regarding model specification. Section 4.5 presents the results, and Section 4.6 concludes. Data and technical details are discussed in the appendix.

4.2 Motivation

The empirical model in this chapter is a technical expansion with more free parameters than fixed loading models. It does not postulate parameter change, but nests a fixed parameter model as well as the variable factor loadings setup.

A fixed parameter model can most easily be understood as a weighted index of the series used to estimate the factor, like an industrial production index. The main difference is that the weights are not obtained from a measure like, for example, value added by industry but endogenously from a maximization of linear dependence between the observables and the unobserved factor. Fixed parameters then imply that the contemporary covariance matrix of the observables as well as the factor's autocovariance function is assumed to be time invariant. The parallel to the work by Burns and Mitchell [1946] is obvious: they postulated the existence of stable lead and lag relationships between economic time series, and accordingly classified all time series according to their leading, lagging or coincident character relative to the business cycle.

Modern business cycle theory has taught us to incorporate stochastics into our models and to remain skeptical about stable dynamic relationships especially in the long term. Several waves of technological innovations have changed America's economy substantially since the Civil War, which leads us to abandon the idea that continuously observed economic time series may stay in a stable relationship with each other. Put simply, the longer the time horizon, the stronger the assumption of parameter stability in a time series model becomes.

The question then remains as to why no contributor to the debate on long-term comparison of U.S. aggregate volatility has recognized this aspect and tried to properly account for it. The answer is most likely the lack of data. Accounting for structural change in national accounting requires annually observed prices of all components to be used to add up aggregate output. In the absence of annual prices, Balke and Gordon [1989] and Romer [1989] used shortcuts to circumvent that problem.

In order to relate to the debate so far, we use our nested model with time invariant parameters, which is likely to behave similarly to the two HNA-based methods. The methodological expansion of this chapter then allows us to abandon the assumption of parameter stability and investigate if it represents a misspecification.

We do that by choosing the parameter for the degree of variability in a Bayesian fashion, starting with an extremely tight prior. This embodies the belief that the economy's structure remains stable. We then offer a choice of parameters that allow for the same degree of parameter change through time but differ in the uncertainty around that presumption; i.e., we experiment with the weight that the prior has in the posterior distribution of the parameter. Starting from one extreme where we reproduce a stable economic structure, we approach step by step the other extreme of a model economy whose structural change is completely determined by the likelihood function and where our prior belief as to how fast the economy may change has no impact.

4.3 Bayesian Dynamic Factor Theory

4.3.1 The Model

Dynamic factor models in the vein of Sargent and Sims [1977], Geweke [1977] and Stock and Watson [1990] assume that a panel data set can be characterized by a latent common component, which captures the comovements of the cross-section, and a variable-specific idiosyncratic component. These models imply that economic activity is driven by a small number of latent driving forces, which can be revealed by estimation of the dynamic factors. A Bayesian approach to dynamic factor analysis is provided, among others, by Otrok and Whiteman [1998] and Kim and Nelson [1999a]. Del Negro and Otrok [2003] describe an estimation procedure for dynamic factor models with time-varying parameters.

Our panel of data Y_t, spanning a cross-section of N series and an observation period of length T, is described by the following equation:

$$Y_t = \Lambda_t f_t + U_t \tag{4.1}$$

where Λ_t is the $N \times 1$ coefficient vector linking the common factor to the i-th variable at time t, f_t represents the 1×1 latent factor and U_t is the $N \times 1$ vector of variable specific idiosyncratic components. The latent factor, which captures the common dynamics of the dataset, is our primary object of interest.[5] We assume that the factor evolves according to an AR(q) process:

$$f_t = \varphi_1 f_{t-1} + \ldots + \varphi_q f_{t-q} + \nu_t \tag{4.2}$$

with $\nu_t \sim \mathcal{N}(0, \sigma_\nu)$ while the idiosyncratic components U_t are assumed to follow an AR(p) process:

$$U_t = \Theta_1 U_{t-1} + \ldots + \Theta_p U_{t-p} + \chi_t \tag{4.3}$$

[5] Generalization to several factors is straightforward but requires additional identifying restrictions.

where $\Theta_1, \ldots, \Theta_p$ are $N \times N$ diagonal matrices and $\chi_t \sim \mathcal{N}(0_{N\times 1}, \Omega_\chi)$ with

$$\Omega_\chi = \begin{bmatrix} \sigma_{1,\chi} & 0 & \cdots & 0 \\ 0 & \sigma_{2,\chi} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{N,\chi} \end{bmatrix}$$

The factor loadings or coefficients on the factor in equation (4.1) Λ_t are assumed to be either constant or (in the time-varying model) to follow a driftless random walk:

$$\Lambda_t = \mathscr{I}_N \Lambda_{t-1} + \varepsilon_t \tag{4.4}$$

where $\mathscr{I}_N$ is a $N \times N$ identity matrix and $\varepsilon_t \sim \mathcal{N}(0_{N\times 1}, \Omega_\varepsilon)$ with

$$\Omega_\varepsilon = \begin{bmatrix} \sigma_{1,\varepsilon} & 0 & \cdots & 0 \\ 0 & \sigma_{2,\varepsilon} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{N,\varepsilon} \end{bmatrix}$$

The disturbances χ_t and ε_t are assumed to be independent of each other.

The dynamic factor in this model is identified up to a scaling constant and a sign restriction. The scale indeterminacy is typically tackled by fixing the variance of the factor innovations σ_v to be equal to a constant (see e.g. Sargent and Sims [1977]).[6] The sign indeterminacy of the factor loadings Λ_t and the factor f_t is resolved by adopting a sign convention; i.e., by restricting one of the factor loadings to be positive (see Geweke and Zhou [1996]). Neither of these two assumptions restricts the information content of the factor model.

4.3.2 Priors

Before proceeding to the estimation of the system, we specify prior assumptions. These priors are informative and have a substantive interpretation in terms of our research question, especially with regard to time variation in the parameters. We adopt priors for three groups of parameters of the above system. These are, in turn, the parameters in the factor equation (4.2), the parameters in Equation (4.3) governing the law of motion of the idiosyncratic component, and the parameters in the law of motion of the factor loadings (4.4).

For the AR-parameters $\varphi_1, \varphi_2, \ldots, \varphi_q$ of the factor equation, we specified the following prior:

[6] We set $\sigma_v = 1$.

$$\varphi^{prior} \sim \mathscr{N}(\underline{\varphi}, \underline{V}_{\varphi})$$

where $\underline{\varphi} = 0_{q\times 1}$ and

$$\left[\underline{V}_{\varphi}\right] = \tau_1 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{q} \end{bmatrix}$$

For the AR-parameters $\Theta_1, \Theta_2, \ldots, \Theta_p$ of the law of motion of the idiosyncratic components, we specified the following prior:

$$\theta^{prior} \sim \mathscr{N}(\underline{\theta}, \underline{V}_{\theta})$$

where $\underline{\theta} = 0_{p\times 1}$ and

$$\left[\underline{V}_{\theta}\right] = \tau_2 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{p} \end{bmatrix}$$

We choose for $\tau_1 = 0.2$ and $\tau_2 = 1$. Both priors imply that we punish more distant lags, very much in the spirit of Doan et al. [1984]. This is implemented by progressively decreasing the uncertainty about the mean prior belief that the parameters are zero as lag length increases.

For each of the variances of the disturbances in v_t and χ_t, we specified the following priors:

$$\sigma_v^{prior} \sim \mathscr{IG}\left(\frac{\alpha_v}{2}, \frac{\delta_v}{2}\right)$$

$$\sigma_\chi^{prior} \sim \mathscr{IG}\left(\frac{\alpha_\chi}{2}, \frac{\delta_\chi}{2}\right)$$

We choose $\alpha_\chi = \alpha_v = 6$ and $\delta_\chi = \delta_v = 0.001$, which implies a fairly loose prior. $\mathscr{IG}$ denotes the inverted gamma distribution.

For the factor loadings, we distinguish two cases. With constant factor loadings (disregarding structural change), the relevant prior for each individual factor loading is:

$$\lambda^{prior} \sim \mathscr{N}(\underline{\lambda}, \underline{V}_{\lambda})$$

where $\underline{\lambda} = 0$ and $\underline{V}_{\lambda} = 100$.

For time-varying factor loadings, we employ the posterior mean from the constant factor loadings model (see the appendix for a description). For each of the variances of the disturbances in ε_t the prior is:

$$\sigma_{\varepsilon}^{prior} \sim \mathscr{IG}\left(\frac{\alpha_{\varepsilon}}{2}, \frac{\delta_{\varepsilon}}{2}\right)$$

Here, α_ε and δ_ε play decisive roles in determining the degree of time-variation in the factor loadings. For $\alpha_\varepsilon \to 1$ and $\delta_\varepsilon \to 0$ our prior is fully dominated by the likelihood function, allowing λ to roam freely without any prior restrictions on the variance of the random walk in equation 4.4. By progressively increasing α_ε and δ_ε relative to the sample size T and $(\Delta\lambda_i)(\Delta\lambda_i)'$ [7], the time variation of λ is restricted more and more and eventually suppressed entirely. Varying the weight put on our prior of constant factor loadings thus enables us to choose the degree of time-variation we think is appropriate.[8]

Three parameter combinations within the factor loadings prior priors implement time variation of the factor loadings. They differ only in the degree of uncertainty about the prior assumptions, but the implied error variance is approximately equal in every case[9]:

α_ε	δ_ε	Uncertainty
1	0.01	high
10	0.1	medium
100	1	low

4.3.3 Estimation

We estimate the model in Bayesian fashion via the Gibbs sampling approach. This procedure enables us to make draws from nonstandard joint distributions by subdividing them into several blocks of standard conditional distributions. In our case, the estimation procedure is subdivided into three blocks. We begin with the initial iteration step: in the first block the parameters of the model $(\varphi_1, \varphi_2, \ldots, \varphi_q, \Theta_1, \Theta_2, \ldots, \Theta_p)$ are calculated by conditioning on the initialized

[7] Here, $\lambda_i = [\lambda_{i,1}\ \lambda_{i,2}\ \ldots\ \lambda_{i,T}]$ and Δ is the first difference operator for this vector.

[8] For $\alpha_\varepsilon = 1000$ and $\delta_\varepsilon = 0.01$, the model replicates the characteristics of the constant factor specification.

[9] The mean of the inverted gamma distribution depending on the parameters is defined by $\delta/(\alpha-1)$ for $\alpha > 1$.

factor f_t and the factor loadings Λ_t. In the second block, conditional on the drawn parameters of the first block and the initialized factor loadings, the factor f_t is computed. In the third and last block of this first iteration, conditional on the drawn parameters and factor we estimate the (possibly time-varying) factor loadings. After the first iteration, we continue with the first block of the following iteration using the calculated factor and the factor loadings from the previous iteration step to estimate the parameters of the model $(\varphi_1, \varphi_2, \ldots, \varphi_q, \Theta_1, \Theta_2, \ldots, \Theta_p)$. Conditioning on these parameter values in combination with the computed factor loadings from the previous iteration, the factor f_t is calculated. In the last block of this iteration step we use the currently computed parameters and factor to calculate the factor loadings Λ_t. In the following, we use the most recent values of the parameters, factor and factor loadings to cycle through further iterations[10]. These iterations have the Markov property: as the number of iterations increases the conditional posterior distributions of the parameters, the factor and the factor loadings converge to their marginal posterior distributions at an exponential rate [Geman and Geman, 1984].

4.4 Data and Empirical Strategy

4.4.1 Data

The data stems almost entirely from the Historical Statistics of the United States [Carter et al., 2006]. There is one series from the NBER Macrohistory Database.[11] Monthly series were transformed to annual series by simple averaging.

The data set contains 53 series which run from 1867 to 1995.[12] It consists of 36 and 17 nominal series, or 27 agricultural and 26 non-agricultural ones. Of the real subset, 19 series represent other sectors than agriculture, and of the 19 non-agricultural real series a further subset of 11 series represents industrial production (mining and metals), while the remaining eight series are population and business failures, number of patents, two transport indicators, export and import volumes for coal and import volumes of coffee.

All series are used in logarithms if they are not already in percentage terms. After detrending, all series are demeaned and divided by their respective standard deviations since the units of measurement are very different. Detrending is

[10] See the appendix for a more detailed description of our estimation procedure.

[11] `http://www.nber.org/databases/macrohistory/contents/`

[12] We have experimented with a longer data set until 2005, but had to reduce the number of series to 47, and could not track the official business cycle turning points satisfactorily anymore. It seems that since the mid-1990s, too many new products have entered the GDP, making our data set insufficient for the third millennium.

performed with the Hodrick-Prescott filter with a smoothing parameter of 6.25 according to Ravn and Uhlig [2002]. We have tried a number of other filters to cross-check the results, ensuring that the conclusions are robust to changing technical details. The appendix delivers a full account of these results.

4.4.2 Empirical Strategy

The drawing from the posterior distributions consists of 220 experiments, since there are 11 subsets, 5 different models (constant factor loadings, and four different degrees of parameter variability) and 4 different filters. The number of draws is 30,000 of which the first 9,000 are burned to reduce the impact of the initial values. Serial correlation between the draws is reduced by saving only every tenth draw, such that 2,100 draws are finally used for inference. Convergence of the conditional distributions is assured by repeating the procedure and comparing the results. Results for convergence checks can be obtained upon request.

The periods of interest here are defined by World War I and II. Throughout this chapter, "prewar" refers to the years 1867-1913, "interwar" to 1914-1945, and "postwar" to 1946-1995.

It is important to explain how we normalize the factor's scale. Since the factor is estimated from filtered series with a normalized standard deviation its own standard deviation is by definition 1 (due to sampling error it may deviate slightly from this value). It is standard procedure to scale the factor's volatility to a value obtained from national accounting, such as 2.01% for postwar NIPA output. Since this study asks for the volatility of 19th century U.S. economic activity, it would be misleading to use historical national accounting results from that period to scale our factor. Thus, we rely only on the undisputed postwar estimate of GNP volatility and fix the factor's postwar standard deviation to this value ($\sigma^{DFM}_{postwar} = \sigma^{GNP}_{postwar}$), but preserve the factor's original ratio $\frac{\sigma^{DFM}_{postwar}}{\sigma^{DFM}_{1867-1945}}$ by scaling the first half of the factor relative to postwar GNP volatility.

Results for relative volatility are discussed within the framework of varying degrees of time variation of the factor loadings; i.e., using four different priors. However, when particular periods are discussed and plots are shown, the specification with the lowest degree of time variation is chosen ($\alpha_\varepsilon = 100$ and $\delta_\varepsilon = 1$) (but still with some time variation), which we think is the most conservative assumption we could make.[13] For an impression of the degree of time variation, see Figure 4.1 which plots the factor loadings for 25 observables and 2 different priors. The dotted lines show clearly loadings with much less high frequency variation. This corresponds to the notion that the basic functioning of the economy is

[13]The respective plots and results from alternative parameterizations may be requested from the authors.

unlikely to change overnight. Note also that not all variables are bound to change their sensitivity to the latent factor (i.e., the weights) quickly, even as the uncertainty about their stability increases. This shows that we have most likely reached a natural upper limit of parameter stability.

4.5 Results

Figure 4.2 presents the American business cycle between 1867 and 1995. The graph shows the summary of the fluctuations of 53 continuously measured time series indicating economic activity. The comparison to Romer's [1989] GNP measure spliced in 1929 with the official NIPA figures shows that our factor's turning points generally coincide with the established boom and bust pattern.

The long upswing until the early 1870s which was connected to, among other things, the construction of new railroads, is visible, as is the following deep and long depression [Fels, 1951]. The factor features the recessions of the mid-1880s as well as of the mid-1890s. We find the deep recession of 1907/8 in the dynamic factor, which Temin [1998] attributed mainly to adverse monetary influences from Europe.[14] Of the cycles in the postwar era, clearly the first oil shock in 1972 is striking. In the postwar years the factor tracks the official statistics well, in spite of its relatively strong reliance on agricultural data.

The most notable differences can be found between World War I and II. First, the recession of 1920/21 is found to be more severe than in Romer [1988], and even more than in Balke and Gordon [1989]. We will discuss this result in detail below.

The second obvious difference is the GNP's peak during World War II which we find to be much smaller than the official statistics claim. This touches on another chapter of American business cycle history, which has not yet been settled. Higgs [1992] summarizes the debate, which started already in 1945 and was initiated by Kuznets [1945]. As the discussion below demonstrates we can support some of the critique on the official statistics.

4.5.1 Volatility Comparison in the Long Run

Column I of Table 4.1 shows ratios of the factor's standard deviation measured from the full set of 53 series. Postwar volatility is placed in the numerator, so that a value above 1 means aggregate volatility is larger after 1945 than before 1914. Additionally, Table 4.1 shows results for identified subsets, such as real

[14] See also Miron and Romer [1990], Davis [2004] and Davis et al. [2007] for discussions of the antebellum business cycle.

Figure 4.1: Factor loadings, 1867-1995. Dotted: $\delta_\varepsilon = 1, \alpha_\varepsilon = 100$, continuous: $\delta_\varepsilon = 0.01, \alpha_\varepsilon = 1$.

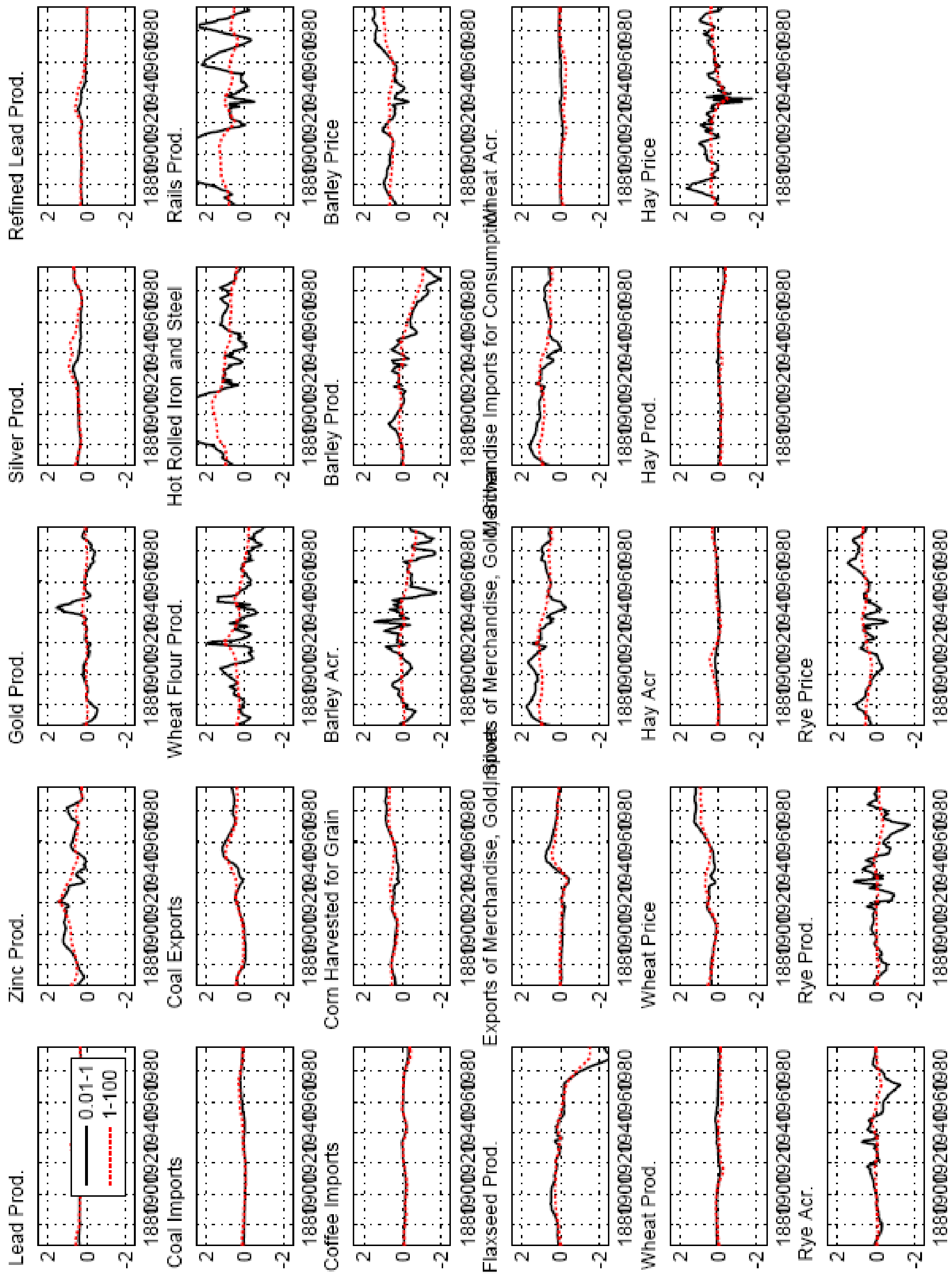
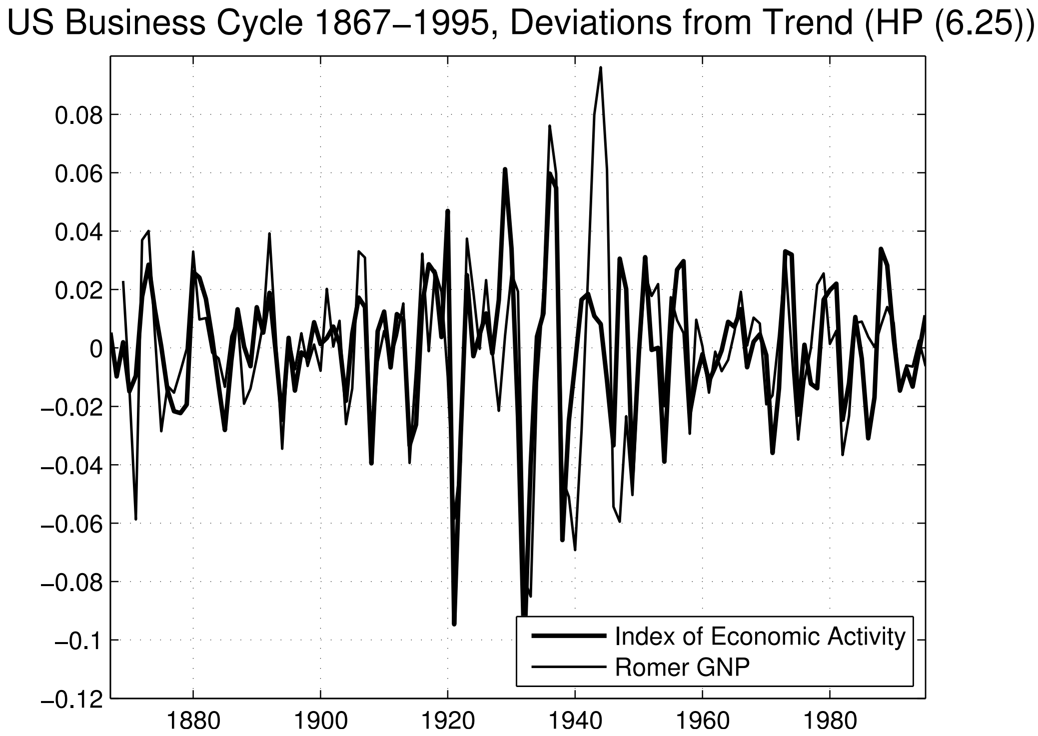


Figure 4.2: The U.S. business cycle 1867-1995. Factor from 53 Series, deviations from trend, HP(6.25) filtered, FL-prior: 1/100.



or nominal series. The rows contain the evidence from different degrees of time-variability as explained above. As two extremes, the figures at the top are results from a model where time variability is left completely to the data, whereas the bottom figures depict quasi-constant model results.[15] Each relative volatility is given along with its median and the standard deviation around can be found in every second column.

Estimating the common factor from all 53 series results in volatility ratios that increase with the amount of time variation of the factor loadings. The constant or near constant model exhibits nearly the same volatility after World War II relative to the period before World War I. Compared to established results, this finding coincides best with Romer's [1989] value of 0.97, while Balke and Gordon [1989] advocate a value of 0.81 or a 19% decline of postwar volatility. However, as we increasingly introduce the possibility of structural change, postwar volatility rises relative to prewar volatility. A moderate degree of time change (1/100) causes a 33% increase of postwar volatility. As the aggregation coefficients are allowed to vary even more in time, a doubling of cyclical activity is easily reached (first row

[15] The results obtained from a classic constant DFM can be found in the appendix.

Table 4.1: Ratios of standard deviation, post-WWII/pre-WWI, factor from HP(6.25)-filtered data.

Subset	I ALL		II REAL		III NOMINAL		IV NON-AGRIC.		V AGRIC.	
N	53		36		17		26		27	
FL Prior	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ
0.01 / 1	2.36	0.30	2.07	0.26	0.84	0.12	1.59	0.18	1.28	0.18
0.1 / 10	1.69	0.19	1.87	0.23	0.85	0.12	1.42	0.16	0.99	0.13
1 / 100	1.33	0.15	1.66	0.20	0.84	0.13	1.34	0.15	1.21	0.16
0.01/1000	1.02	0.07	1.17	0.02	1.29	0.10	0.92	0.06	1.23	0.09

Subset	VI NON-AGRIC. REAL		VII NON-AGRIC. NOMINAL		VIII AGRIC. REAL		IX AGRIC. NOMINAL		X NON-AGRIC. REAL PROD.		XI NON-AGRIC. REAL NON-PROD.	
N	19		7		17		10		11		8	
FL Prior	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ	Ratio μ	σ
0.01 / 1	1.77	0.24	0.72	0.11	0.78	0.12	1.04	0.10	1.33	0.18	1.33	0.20
0.1 / 10	1.60	0.21	0.83	0.13	0.65	0.09	1.02	0.15	1.21	0.14	1.37	0.19
1 / 100	1.52	0.18	0.88	0.12	0.74	0.11	1.12	0.16	1.30	0.18	1.09	0.16
0.01/1000	0.90	0.07	1.32	0.02	2.33	0.03	1.24	0.09	0.86	0.06	1.38	0.03

Medians (μ) and standard deviations (σ) reported.

in Column I).

These results suggest that postwar volatility moderation is connected to the choice of a constant parameter model. Even a very low degree of structural change (as the parameter combination $\delta\varepsilon = 1$ and $\alpha_\varepsilon = 100$) favors the view that prewar volatility was low compared to the experience after World War II. Thus, admitting that the assumption of no structural change is stronger than the assumption of at least some change casts considerable doubt upon the view of a postwar business cycle that is smoother than before the two World Wars.

We deployed a number of robustness tests to validate this result. As the data set contains a number of nominal series, it is advisable to repeat the exercise concentrating only on real activity. The literature on factor analysis of economic activity is divided as to how to do this best: a non-structural approach is to extract more than one factor from the full dataset, forcing the second factor to be orthogonal to the first one. This procedure is generally seen as yielding good characterizations of real activity by the first factor, and of nominal conditions by the second factor. A more structural alternative to be followed here is to restrict factor loadings a priori by exclusion restrictions. We do so by identifying the full data set *ex ante* into 36 real and 17 nominal series.

A short digression seems appropriate here. The nature of GDP in constant prices and the identified real factor are fundamentally different. While prices are needed in national accounting to compare production measured in different units, comovement can be estimated from volume series directly. A dynamic factor aggregate is therefore independent from relative prices that determine the weight of production volumes in GDP. Discussing this issue, Romer [1988] found that using 1929 relative prices in contrast to 1982 prices is responsible for overweighting the volatile components of GDP in the Commerce Department's measures of 19th century volatility. DFM is immune to this source of bias, because it finds aggregation weights independently of relative prices. By restricting the sample to real series and allowing the weights to change we aim directly at the core of the problems associated with HNA-based volatility measurement.

As Column II in Table 4.1 bears out, focusing on real series emphasizes the conclusion from the mixed data set. Keeping relative weights constant, real business cycle volatility is not smaller after World War II relative to before World War I.[16] Allowing for structural change, postwar volatility rises relative to prewar volatility, suggesting that the assumption of constant weights over the World Wars favors the moderation view, while even small degrees of structural change point toward the direction of an increase of business cycle volatility after World War II.

As Christina Romer pointed out in several of her papers, prewar measures of volatility rest almost entirely on commodity output as it is very often the only data available that can be used in HNA. Historical national estimates of the period before 1909 (such as the Commerce series criticized by Romer) still overemphasize manufacturing due to lack of data from other sectors. This problem may be resolved or at least alleviated by dynamic factor models. They can exploit the informational content in data that does not fit into the national accounting framework, and therefore help overcoming the small choice of non-industrial time series recorded for the time before World War I.

Conversely, adding too much agricultural information may bias the series toward a sector which is typically not regarded as comoving strongly with the overall business cycle. It turns out, however, that this is not the case. Estimating relative volatility from continuously recorded non-agricultural production series mirrors the results obtained above. Column VI focuses on real series from the industrial and the service sector (which are mainly from the transport sector and

[16]Obviously, here it is larger but evidence from Christiano-Fitzgerald filtered series shows a value below 1 in the constant case. It exceeds 1 only when the loadings can change.

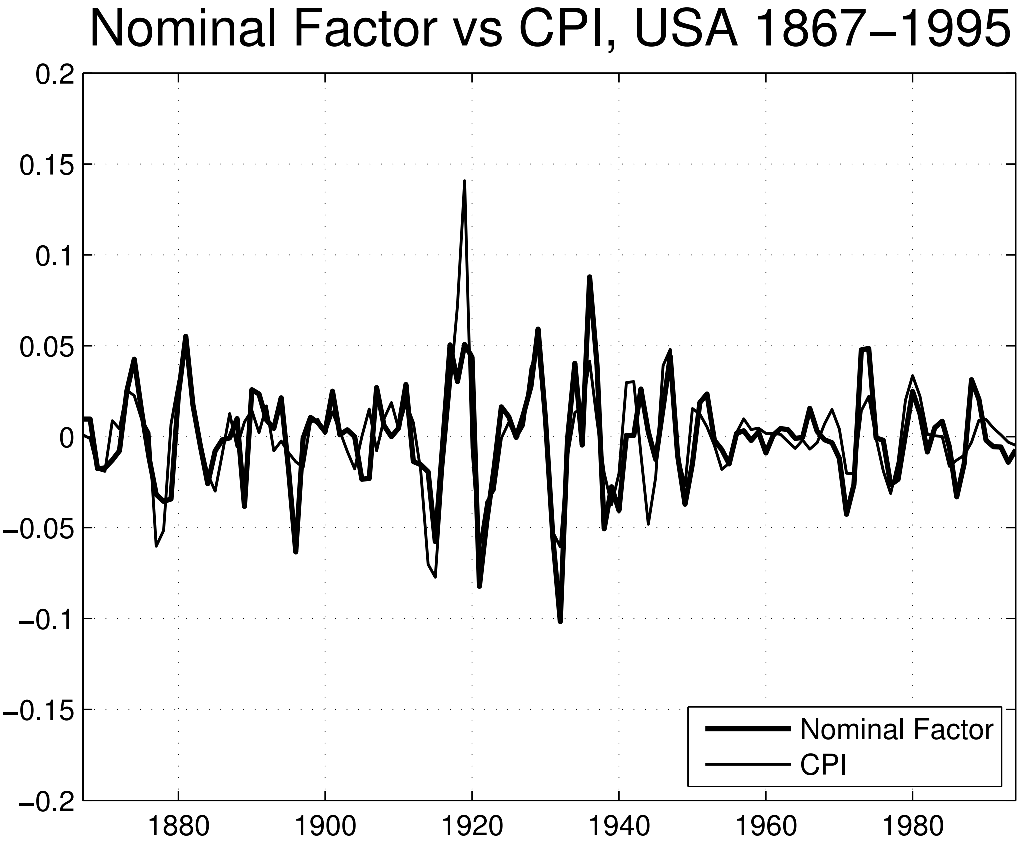
not from public services). While the near-constant model at the bottom shows a 10% decrease in postwar volatility, adding a small degree of flexibility in the model reverses the picture completely, and the ratios increase well above 1. A similar picture emerges where only production volumes series are analyzed (Column VIII). We may conclude from this exercise that our result is robust to changes of the underlying data.

Having said that, let us consider the nominal subset which consists of 17 series. It exhibits lower postwar volatility if structural change is assumed to be the relevant model. The third column in Table 4.1 summarizes that finding. Starting from the near-constant parameters model, volatility after World War II was 20-30% higher than pre-World War I volatility. Allowing the factor loadings to move firmly over time leads however to a decrease in the ratio of postwar to pre-World War I volatility. This is a strong result considering the monetary disturbances associated with the oil shocks in the 1970s. Figure 4.3 provides some clues as to why this may be so: nominal volatility in the 19th century seems to be concentrated in the immediate postbellum years that is characterized by the greenback's convertibility suspension and uncertain expectations about the metallic standard of the dollar [Calomiris, 1994]. The postwar years, meanwhile, experienced a very stable monetary period in the 1960s and similarly in the 1980s and 1990s.

In light of the literature this result seems to be a confirmation of traditional stylized facts about nominal business cycle volatility that were challenged by Balke and Gordon [1989]. Using new consumer price data they presented a novel GNP deflator which is substantially more stable before World War I than previous deflators. If this was true, prices and wages would not have become more rigid after World War II as is widely believed [Sachs, 1980]. Our finding using continuous price and value series for the whole period 1867-1995, and allowing for a moderate degree of endogenous weight adjustment through time, seems to confirm the traditional view. This result reflects one of Allen's [1992] findings about the role of constant and time-varying weights in aggregating individual series to a wage index. He found that applying constant instead of time-varying employment shares leads to less volatile prewar wages. In turn, by using time-varying weights, more prewar volatility is found, leading to reduced postwar wage volatility [Allen, 1992, p. 135f].

We argue that less nominal postwar volatility (or higher rigidity) may partly explain the increased real postwar volatility. Romer [1986a], taking the increase of postwar price rigidity as given, saw them as possibly counteracting the forces of stabilizing government activity. If our specification with slowly changing parameters is the correct one, we have to conclude that the destabilizing forces of price rigidity would by far outweigh anticyclical activities.

Figure 4.3: Factor from 17 nominal series vs U.S. CPI. Deviations from HP(6.25) trend, FL-prior: 1/100. Factor standardized to standard deviation of detrended CPI (1946-1995) of 1.62%. CPI annualized and shifted forwards by 1 year.



4.5.2 Volatility Comparison Over World War I

The debate over how much aggregate volatility varied before and after World War I is to a large degree characterized by Christina Romer's contributions [1988, 1989]. She argued that the 1920/21 recession was less deep than what the Commerce Department's historical GNP series suggests. Thus, she rejected the idea that decreased aggregate demand caused the severe downturn. In contrast to Romer, Balke and Gordon [1989] reported a more severe trough.

As Figure 4.4 shows, we find that volatility increase after World War I was stronger than even Balke and Gordon [1989] posited. The upper panel plots the factor from 1867-1929 against Romer's real GNP measure (1989), the lower does the same with Balke & Gordon's (1989) GNP estimate, all in deviations from an HP-trend. Note that aggregate variability of Romer's GNP estimate before World War I is less than Balke & Gordon's, especially in the 1890s and during the 1907

Table 4.2: Volatility comparison over World War I (1867-1929).

	1867 – 1913 Std. Dev.	1914 – 1929 Std. Dev.	1867 – 1929 Std. Dev.	*Postwar/ Prewar*
GNP Estimates				
Romer	2.07	2.78	2.25	1.3
Balke-Gordon	2.47	4.10	2.96	1.7
Factor: All 53 Series				
0.01 / 1	1.28	5.54	2.96	4.3
0.1 / 10	1.92	4.98	2.96	2.6
1 / 100	2.00	4.88	2.96	2.4
0.01 / 1000	1.83	5.08	2.96	2.8
Factor: 36 Real Series				
0.01 / 1	2.02	4.86	2.96	2.4
0.1 / 10	2.21	4.60	2.96	2.1
1 / 100	2.28	4.50	2.96	2.0
0.01 / 1000	2.21	4.61	2.96	2.1
Factor: 17 Nominal Series				
0.01 / 1	2.24	4.55	2.96	2.0
0.1 / 10	2.29	4.46	2.96	1.9
1 / 100	2.38	4.32	2.96	1.8
0.01 / 1000	1.91	4.98	2.96	2.6

Numbers except ratios in %, and rounded. Only medians reported.
Factor normalized to Balke&Gordon's std.dev. of 2.96%.

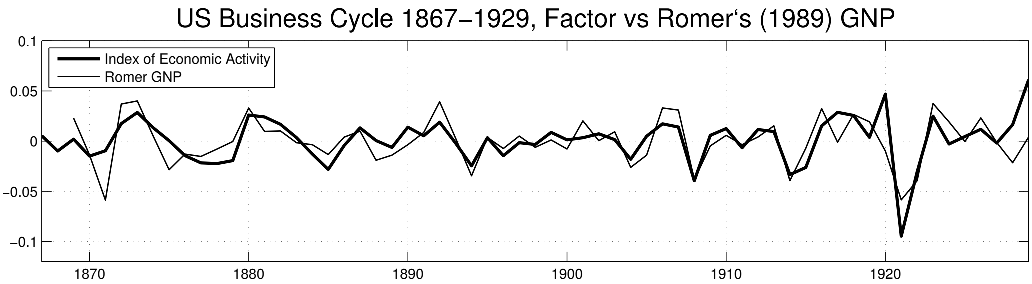
crisis. Different views also exist on the first major postwar depression in 1921 when, according to Balke & Gordon, output was pushed down by almost 9% relative to trend compared to only 5% according to Romer [1989].

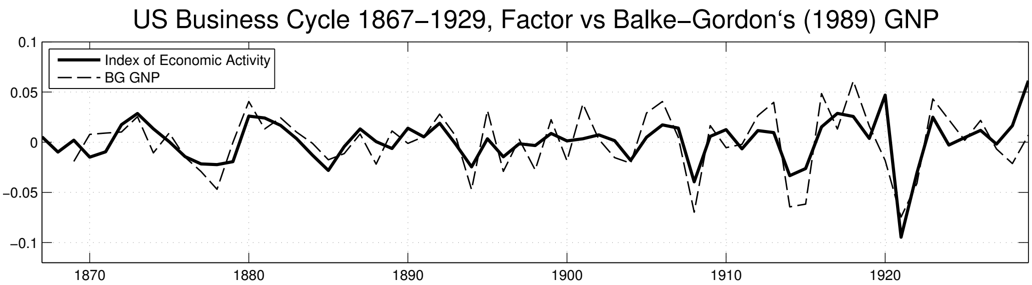
Table 4.2 makes the outcome more explicit. The volatilities of the rivaling GNP in the period before 1914 are 2.07% (Romer) and 2.47% (Balke & Gordon), again expressing Romer's claim of a smooth 19th century business cycle, and Balke & Gordon's rejection thereof.

Fixing the factor's standard deviation between 1867 and 1929 to Balke & Gordon's estimate of 2.96%, our factor shows less time variability for the prewar years than those of Romer and Balke & Gordon. For the time after World War I, however, the experiment clearly leads to a different picture of how much aggregate activity fluctuated. While Romer proposed a 30% increase in volatility between the periods 1914-29 and 1869-1913, we find a much stronger increase of 180% with the near-constant parameters model, which is also considerably larger than Balke & Gordon's assertion of a 70% increase.

Other than in the long run comparison, expressing different prior opinions about how much the aggregation weights change over time does not reveal a monotonous relationship between the volatility ratio and the degree of time variability of the factor loadings. However, a clear-cut conclusion still offers itself. Allowing the weights to change moderately (1-100) reduces post-World War I fluctuations relative to the prewar years although not below Balke & Gordon's or even Romer's values. All other parameterizations lead to even higher volatility increases over the war. Thus, using continuously recorded series and evidence from a setup which is not harmed by the usual criticism against historical national accounts, lead us to believe that the 1921 recession was indeed very deep and not a figment of the data.

Figure 4.4: The U.S. business cycle 1867-1929, compared to GNP-estimates. Factor from 53 series, deviations from trend, HP(6.25) Filtered, FL-prior: 1/100.





4.5.3 The U.S. Business Cycle Over World War II

Although official national accounts were available from 1929 onwards, not all of the reported business cycle turning points remained undisputed. National income estimates during World War II were strongly criticized for their conceptual and statistical underpinnings. The discussion started already during the war and was initiated by contemporaries such as Simon Kuznets [1945], and Wesley Mitchell [1943], among others.

Two main points of critique have evolved during the discussion: that the official figures for real income were not appropriately deflated, and that war outlays may be regarded as intermediate products and therefore should not be part of aggregate income [Higgs, 1992, p. 45].

The most radical position regarding that question was formulated by Kuznets [1945], who calculated GNP without any war outlays for rhetorical purposes. An intermediate view treats war expenditure as adding to consumer welfare in the sense that it helps to preserve the social body of a nation but only in an exceptional period of self-defense. Kuznets accepted that view, but only for temporary periods, while the consensus view extended that concept to a permanent state, partly because of the Cold War [Higgs, 1992, p. 47]. Disagreeing with that general notion, Nordhaus and Tobin [1972] dissented from that consensus view and corrected the standard GNP measure for all war outlays. The measure used here is Variant III from Kuznets [1961, p. 487], which uses war expenditure only insofar as it adds to the military capital stock that theoretically may be used for non-defense purposes after the war. The deflator, however, is the same as used by the Commerce Department for reasons of long term comparability [Kuznets, 1961, p. 470f].

The question of accounting for military expenditure is a good example for the complementary relationship between factor models and national accounting. While national accounting aggregates are constructed for a particular purpose, such as the one debated here, a dynamic factor is merely an indicator of the state of the economy, and thus less controversial. In cases of insufficient data, an indicator method has the potential to give better quantitative directions than a hard-to-obtain national accounting aggregate.

An activity index such as a dynamic factor may also remedy the problem of unobserved inflation, which is connected to the fact that the U.S. economy was rather a command economy than a market economy, and therefore prices did not reflect the real value of the goods purchased. Since prices are needed for aggregation in national accounting, it is almost impossible to construct a good representation of real output. An identified real dynamic factor does not need prices for aggregation and therefore does not suffer from this problem.

Let us focus on the years 1929 to 1949, and compare the official national accounting figures with an alternative estimate by [Kuznets, 1961, p. 481]. It approaches the GNP from the income side, and treats especially war expenditures differently. The upper panel of Figure 4.5 plots the factor (thick line) against the national income and product accounts, the backbone of the U.S.'s official statistics. The detrending was done with a Hodrick-Prescott filter with a λ of 6.25. In the lower panel, Kuznets' income estimate is shown (broken line). The prior we used for the graph is the same as for the graphs above and allows for some variation of the factor loadings, but not in a large scale (1/100).

The factor (thick line) is the ex ante identified real factor from 36 series as described above. Its volatility is normalized to NIPA's standard deviation for 1946-

1995 with a proportional scaling of the years 1929-1945.

A quick glance receives the message: until 1938 the factor's business cycle timing is very close to both the standard output measure and Kuznets' income estimate. While the Commerce Department's aggregate continues to decline, however, both the factor and Kuznets' alternative (lower panel) have reached the lower turning point. The subsequent rise could narratively be described as the recovery from the Great Depression, lasting until 1941 (factor: 1942).[17] The war economy, fully set in motion during after the attack on Pearl Harbor in December 1941, delivered a great deal of military goods but failed to maintain the level of consumer goods needed to satisfy the population at the home front. In 1945, the lower turning point is reached by both measures, and their subsequent rise could be attributed to the redistribution of war-related productive capital which created a strong recovery.

The official story sounds fundamentally different: from the lower turning point in 1940, there was an unprecedented rise in real output until 1944 – almost at the end of the war and one year before the factor and Kuznets' aggregate have their lower turning point. At the peak of war production, the economy fell into a recession which lasted throughout the postwar years until 1949.

There are good reasons to believe that the closeness of the factor to Kuznets' alternative measure of national income is not a coincidence but that both series represent actual cyclical activity better than the official figures and therefore resemble each other. Kuznets' estimate is intended not only to account for the war related surge in commodity output but also to reflect consumption opportunities at the home front more accurately. Therefore it includes only military expenditure for durable goods that may be usable for non-defense activities after the war.[18] The real factor contains a number of broadly based business cycle indicators, and single activity indicators such as the number of business failures which are likely to reflect real consumption opportunities better than the Commerce Department's estimate.

This result is robust to the prior we formulate for the factor loadings' variability when obtaining the factor only from real series. When including nominal series and working with the full set, however, we arrive at a damped business cycle in the case of a strong prior as shown here.[19] It shows only approximately 2% activity

[17] Vernon [1994] discusses the role of fiscal and monetary policies before 1942 for the recovery.

[18] Both Kuznets' Variant III and the Commerce Department's series suffer from the choice of a deflator which underestimates inflation throughout the war and overestimates it in the immediate postwar years [Kuznets, 1952]. However, Kuznets reverted back to the Commerce Department's deflator for purposes of long run comparability [Kuznets, 1961, p. 471]. The identified real factor is immune to that discussion. Further research, however, should investigate Kuznets' claim in the light of dynamic factor evidence.

[19] Compare Figure 4.2.

above trend throughout the war, a small dip at the end of the war and a postwar recovery similar to the version shown here. Despite its damped behavior it is still much closer to Kuznets' income estimate than to the official NIPA figures. It does not change the broad picture presented here, and may be an interesting subject for further analysis.

In summary, while business cycle timing generally is not a subject of strong debate in American history, in this case it is. Dynamic factor models have proven to be excellent business cycle indicators in the presence of abundant data [Stock and Watson, 1998] as well as when data is scarce [Gerlach and Gerlach-Kristen, 2005]. The cyclical behavior of the factor leads us to follow Kuznets (and others) who called for a revision of the official historiography of the American business cycle during World War II.

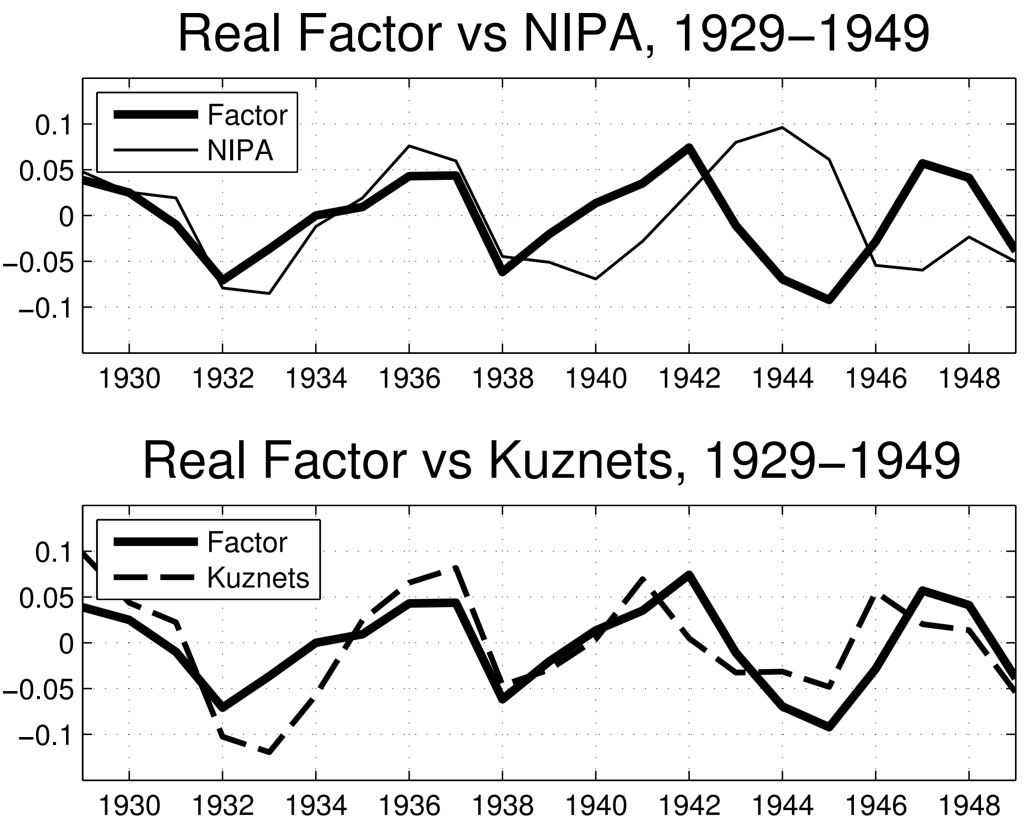


Figure 4.5: Rivaling estimates of GNP during World War II vs a dynamic factor (from 36 real series, deviations from trend, HP(6.25) filtered, FL-prior: 1/100.

4.6 Conclusions

Factor analysis of aggregate economic activity represents an appealing alternative to Historical National Accounting whenever the data is incomplete or plagued by structural breaks. In this chapter, we re-examine the volatility of historical business cycles in the U.S. since 1867. We present both a comparison between the pre-World War I and the interwar period, and the long-term perspective from the classical gold standard era to the late 1990s.

Our main findings are that the business cycle prior to World War I was even less volatile than previously thought, and was quite plausibly no more volatile than the postwar business cycle. We also find pervasive evidence that the interwar years, in particular the period immediately following World War I, were more volatile than has been maintained in the more recent literature. This would make the Great Depression of the 1930s less of a historical singularity.

For the years surrounding World War II we find indications that the standard figures for national output misrepresent the true business cycle timing, and that the U.S. economy underwent a downturn after mobilization and a strong postwar recovery.

Many of our findings derive from the analysis of time variation in factor loadings, or the weights assigned to the various individual series when constructing the index of aggregate economic activity. To this end, we employed a Bayesian approach to factor analysis, iterating over the likelihood function by Gibbs sampling. We nest both a constant loadings model and a time-varying parameter setup with varying degrees of time change. We find time-varying factor loadings to be an effective way of dealing with the structural changes in the U.S. economy, a problem that is hard to address in HNA approaches. As a result, we suspect that spurious volatility in national accounts of the U.S. business cycle is not so much a problem of missing or too narrow data. Rather, it seems due to the inflexible weighting schemes underlying most work in national accounting with historical data.

We also chose a more structural approach, restricting our data to load into one real and one nominal factor separately. It is especially the real factor that exhibits a volatility increase after World War II compared to the 19th century even when allowing only for a small degree of parameter change. The nominal factor, however, is found to have become less volatile in the postwar era when compared to the period before World War I once aggregation weights are allowed to vary. When loadings are fixed, however, we arrive at the result by Balke and Gordon [1989]: less real postwar volatility, but substantially more nominal fluctuations.

A loading restriction on agricultural and non-agricultural series substantiates that our main results are not driven by the primary sector. Instead, the dynamic factor model loads heavily on industrial series and therefore couples economic intuition with statistical precision.

Chapter 5

World and National Wheat Market Integration in the 19th Century

5.1 Introduction

Although market integration is one of the subjects in 19th century economic history that has drawn much attention, there is still room for improvement in terms of analytical tools. As more prices become available, demand for dynamic methods that can accommodate large cross-sections of price data increases. The origin of market integration – local, national or international – becomes a matter of interest as data increases in the cross-section.[1]

This chapter draws from the literature on international business cycles and uses its tools for market integration research. Bayesian dynamic factor models are especially promising, since they measure comovement of many time series and go beyond bivariate comparisons.[2] Their complexity therefore grows only proportionally in the cross-section and along the time axis, but not exponentially as that of bivariate models including almost all cointegration frameworks. The dynamic setup allows for quantifying the share of price fluctuations due to world price movements, changes in national market conditions and local shocks.

Applying comovement analysis to 19th century European and American wheat prices shows that the U.S. experience after 1870 was perhaps not particularly revolutionary to world wheat trade in contrast to what the established convergence literature à la O'Rourke and Williamson [1999] suggests. It seems to be fair instead to speak of a major producer accessing the world's biggest market for wheat

[1]GAUSS code for the model used here is available from Chris Otrok's website at `http://people.virginia.edu/~cmo3h/research/wfac3b.prg`. The code with the necessary modifications is available from the author upon request.

[2]The dynamic factor is referred to as common component in this chapter.

– Western Europe, including the U.K. The results also call for reconsidering the relation of national and international market development as their respective timing turns out to be diverse.

The largest boost toward global wheat market integration occurred before 1860, according to the results obtained here, before the railroad or the steamship could have had substantial effects. In the last quarter of the 19th century world wheat market integration accelerated further, but at a slower pace than before 1860.

The next section motivates comovement analysis taking into account historical and technical considerations. Section 5.2 provides a discussion of the relevant methodological literature. An intuitive introduction into the method followed by a formal description can be found in Section 5.4. Section 5.5 describes the data, while Section 5.6 explains the findings. The last section concludes. The appendix contains details about the estimation and discusses some data issues.

5.2 Motivation

The main focus of market integration research in the past three decades or so was on transatlantic market integration after 1870 [Harley, 1980, O'Rourke, 1997]. The main argument stated that markets on both sides of the Atlantic merged because of lower transport costs, which resulted in declining price differences.

In the past few years scholars have begun to gather data from more markets spanning longer periods and applied improved econometric tools, mainly based on cointegration or price dispersion [Jacks, 2005, Federico and Persson, 2006, Persson, 1999, Sharp, 2008]. The methodological arms race was aimed at accommodating the increasing amounts of data in a meaningful way and resolving the question as to how market integration should actually be measured.[3] However, the curse of dimensionality has not yet been overcome, at least in the case when dynamic relations are to be accounted for. Most methods rely on bivariate comparisons cause the amount of parameters to increase exponentially in the number of markets. The complexity of the method proposed here grows linear in data size and allows for studying a large number of markets over a long period incorporating dynamic relationships between prices.

Federico [2008] proposes to use the coefficient of variation as a measurement tool for market integration. While this method can handle many markets, it does not incorporate dynamic relationships. The obvious patterns of covariance in commodity prices are not exploited. Comovement analysis uses these patterns to estimate an unobserved common component that is used as a bench-

[3]Federico [2008] discusses the most popular methods so far.

mark against which each single price is compared. This corresponds directly with Federico's [2008] critique of bivariate price comparisons. He calls for comparing prices against a hypothetical world price. Interestingly, this is exactly in the spirit of Veblen [1893] who discussed wheat prices after the American Civil War in the very first issue of the *Journal of Political Economy*. Thus, there appears to be a long tradition of analyzing local wheat prices on the basis of a latent world price. With this chapter I aim to abandon the purely technical need to use bivariate comparisons and contribute to reviving a more intuitive approach of analyzing market prices across time and space. As methods based on the coefficient of variation go to a certain extent in that direction, they cannot track each market's development over time, which is a natural feature of comovement analysis.

Ejrnaes et al. [2007] use a multivariate error correction model that explicitly incorporates dynamic relationships. However, it is restricted in the cross-sectional dimension as its complexity grows exponentially with the the number of time series. Since it is based on cointegration, this and related classes of models rely on assumptions about the asymptotic properties of unit root tests. The model I propose uses Bayesian econometrics enabling my results to hold even if the sample is not representative for the whole population or the unit root properties of the data are not guaranteed [Uhlig, 1994].

There has been a recent revival of an older discussion about the reason for decreasing price gaps in the Atlantic trade between Knick Harley [1988] and Douglass North [1958, 1968]: North repeatedly rejected the advantage of steam power and metal hulls in decreasing freight rates, and claimed that organizational improvements played a more important role in lowering transport costs and spurring change in international market integration in the first half the 1800s. According to recent studies important steps toward integration have indeed occurred before railroad, intercontinental steam ships and the telegraph could have had substantial effects. Wars and trade policy are instead suggested as important driving forces of market integration [Persson, 1999, Federico and Persson, 2006, Jacks, 2005].

Brautaset and Grafe [2005] present another argument that is based on constant transport technology. They propose scale economies in market efficiency as an explanation for market integration. That is, costs per unit go down as volumes of trade go up, holding technology constant. Some of my results favor this explanation as will be shown in this chapter.

However, this debate only centers on the supply side of the market for trade services. What about the demand side? In the absence of transport cost changes, trade may still increase and price gaps decrease if the relationship between supply and demand changes. Sharp [2008] claims that the main reason for declining price gaps between the U.K. and the U.S. was the increase of American wheat supply. This issue needs to be discussed at the national level as well. Kopsidis [1998] argues that industrialization creates urban demand for agricultural goods, and leads to regionally integrated markets holding agricultural and transport productivity constant. This theory may explain national differences in the timing of the relative development of national and international market integration. The conventional view – using transport costs as the main argument – is that national markets integrate first, since relatively short distances imply low transport costs, and then international trade links are created as technology reduces the cost of distance. However, this order could be reversed. In developing economies some cities may already be linked quite well to international wheat trade due to, for example, a strategic geographical location, while land-locked rural areas are separated from national and international wheat trade. As industrialization sets in, urban demand increases and nationwide specialization begins, fostering national markets on the basis of international integration.

The feature distinguishing this study from others is that it truly differentiates between national and international integration. It can focus on single markets while keeping an eye on the aggregate development. Section 5.6 therefore delivers a number of new results about national integration in an international context.

5.3 Related Literature

Various uses of the common component approach in market integration research can be found. Qin et al. [2006] used a dynamic factor in a vector error correction model (VEC) as an aggregate of all "foreign" prices and compare it to an observed "home" price. By doing so, they augmented the VEC model to the multivariate case. My model is simpler. It conceptualizes the common component or factor as a manifestation of the comovement of prices in different markets and therefore as a manifestation of the law of one price.

Common factors can also be used in panel cointegration frameworks to increase the power of multivariate unit root tests, which goes back to Bai and Ng [2004] and Pesaran [2007]. Applying this method in a recent study on German regional prices levels, Dreger and Kosfeld [2007] found a persistent lack of price convergence among German regions in the period from 1995 to 2004.

Principal component analysis has been used by Sánchez-Albornoz [1974] in a truly pioneering study. He analyzed annual Spanish wheat and barley prices between 1856 and 1889 and focused on the causal effects of wheat trade between regions. He identified regions along geographical and agricultural borders, but could not model the dynamic relationships contained in the data. Thus, in later studies he began to use univariate time series analysis and abandoned the common component approach.

Moreover, there is a strand in the international finance literature similar to what I am pursuing. Bekaert and Harvey [1995] proposed a time-varying measure for integration of national markets into the world market for capital assets. The set of country price returns in their model is explained jointly by a world benchmark portfolio and idiosyncratic country risk. The varying degree to which each of the two factors explained the returns was interpreted as a measure of world capital market integration, which is comparable to the latent factor of all prices in my chapter.

Technically, this study is closest to Kose et al. [2003], although their research interest is not directly related to mine. They estimated the common component of output, consumption and investment between 1960 and 2001 for the G7 countries, and identified a world component and national components. I work with practically the same model but my focus is on price data and market integration.

The relation between international business cycle transmission and world market integration is obvious. Both describe different strata of globalization. While I measure market integration as it is manifested in the price comovement of a traded and crucial commodity, business cycles represent integrated markets subject to common output variations.[4]

Thus, it is appropriate to cite a recent paper that applies dynamic factor models to identify long run business cycle comovement between four Latin American economies starting in the last quarter of the 19th century, i.e., Argentina, Brazil, Chile and Mexico [Aiolfi et al., 2005]. It finds strong exogenous shocks on the cyclical activities of Argentina, Chile and Mexico. Brazil was obviously better insulated from external influences. It remains a field of future research if this result is reflected in the behavior of traded goods in these countries.

A large body of literature utilises mixed sets of time series, i.e., prices and volumes, where either the common component is interpreted as the business cycle, or nominal and real common components are identified [Stock and Watson, 1998]. An application of a single component model to historical time series is described in Sarferaz and Uebele [2007].[5]

One further application to price series is Reis and Watson [2006]. They interpret the common component of a consumer basket of prices as the part of price fluctuations whereas relative prices stay the same [Bryan and Cecchetti, 1993]. They use it to analyze the degree of money neutrality and find that prices were not neutral in the U.S. after 1960.

[4]The theoretical literature is not entirely conclusive about the correlation of trade flows and output variations, and I do not attempt to contribute to this question.

[5]See Chapter 3 of this thesis.

5.4 The Model

5.4.1 Intuition

Comovement measures synchronous price movements in large cross-sections. It has a certain similarity to correlation, the main difference being that correlation is defined over pairs. Another important difference is that comovement measures linear dependence not only in a given period but across time. It represents the whole spectral matrix of leading and lagging correlations [Kose et al., 2003, p. 1218].

While correlation can be understood as a simple bivariate counterpart of comovement, convergence captures a different aspect of relative prices. Take for example Harley's [1980] classic paper about convergence among U.K. and U.S. wheat prices in the second half of the 19th century, which begins with a graph showing a shrinking price gap between Chicago wheat and the British Gazette price (Figure 5.1). Harley, as well as other scholars succeeding him, refers to this closing gap when defining market integration [O'Rourke and Williamson, 1999]. However, Figure 5.1's second striking element – which Harley does not discuss – is the degree of correlation between the two prices. This element is another important feature and thus used as the main argument in this chapter.

Figure 5.1: Price convergence between Chicago and Britain [Harley, 1980].

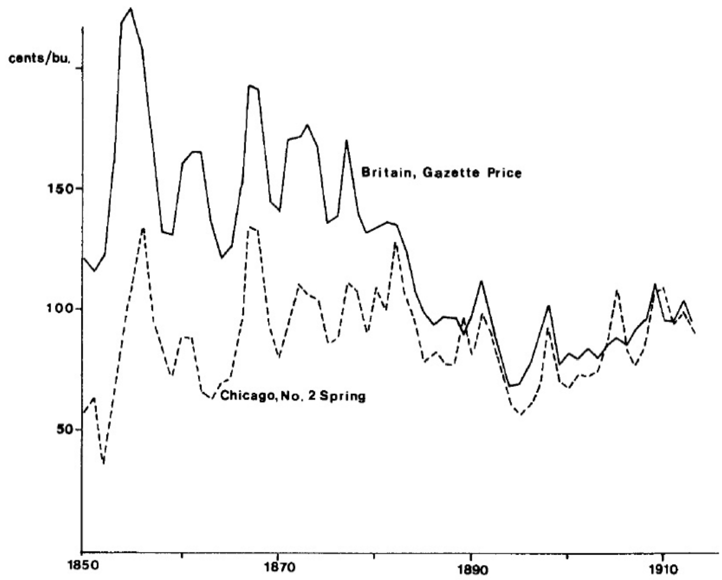


FIG. 1. Wheat prices: Chicago and Britain, 1850–1913.

This bivariate comparison can be carried out for more than two markets by comparing all single series with a benchmark series that represents maximum comovement of all observed series. Consider a simple steady state example. Imagine splitting up each single price p_i into a part c that is the same in all markets and a part u_i that is the deviation from c:

$$p_i = c + u_i \tag{5.1}$$

The common part c could be any rational number, but optimally it should be the one that minimizes the sum of the deviations u_i. For the sake of the argument, the mean over all prices p_i could be chosen, and the absolute deviations u_i could be expressed in percentage of p_i to show how much the common price element explains in each market i. An example is given in Table 5.1.

Table 5.1: Numerical example of common component.

Price	Common Component	Deviation	Absolute Percentage Deviation
p_i	c	u_i	$\|u_i\|/p_i$
3.41	3.00	0.41	12%
2.67	3.00	-0.33	12%
2.95	3.00	-0.05	2%
2.29	3.00	-0.71	31%
3.00	3.00	0.00	0%
5.08	3.00	2.08	31%
3.45	3.00	0.45	13%
1.85	3.00	-1.16	63%

In the left Column of Table 5.1 the observed prices are given. An arbitrarily chosen common component is given in Column 2 and the respective deviations in Column 3. Column 4 contains a normalized measure of how well the common component explains single prices in Column 1. The lower the percentage number, the more the common component explains single prices.

This is an example in the steady state, but what if we include dynamics? How would the common component change if the prices in Column 1 changed? These questions are answered in the following formal discussion. It starts with a dynamic extension of Equation 5.1.

5.4.2 Single Common Component

Given the relation between N prices and their common component in time t, consider what happens if all prices changed in the same direction and to the same degree. In this case their variation should be only due to the common part c but not the remaining part u_i, $i = 1, \ldots N$. If some prices changed to a different degree or in different direction from the others, the common part will explain only a fraction of the price variation and the rest will be due to the specific component $u_{i,t}$. Thus the dynamic formulation of Equation 5.1 for each $p_{i,t}$ is

$$p_{i,t} = a_i + \lambda_i c_t + u_{i,t} \tag{5.2}$$

Here c_t represents the common component, which is the same for all markets and therefore not indexed by i. There is a constant a_i and a weight λ_i that links the common price component to the i-th variable. $u_{i,t}$, the idiosyncratic or specific component, accounts for local, market specific influences, e.g. local crop failures or temporary demand fluctuations.

However, the idiosyncratic parts may experience their individual dynamic processes, i.e., they may be serially correlated, which is expressed as an AR(p)-process:

$$u_{i,t} = \theta_{i,1} u_{i,t-1} + \ldots + \theta_{i,p} u_{i,t-p} + \chi_{i,t} \tag{5.3}$$

Equation 5.2 resembles a linear regression, only that we do not observe the regressor c_t. We can instead describe c_t's dynamics by an AR(q)-process and treat it (together with Equation 5.3) as the transition equation in a state space model:

$$c_t = \varphi_1 c_{t-1} + \ldots + \varphi_q c_{t-q} + \nu_t \tag{5.4}$$

These three equations describe the basic setup. However, since many, not only one, common components are strived for, Section 5.4.4 extends the model to the case with K common components. In Section 5.4.5 I will show how the model parameters and the common component can be estimated. The error term assumptions will be discussed next.

5.4.3 Error Term Assumptions

The local market shocks $u_{i,t}$ are assumed to be normal and uncorrelated in the cross-section:

$$E\left[u_{i,t} u_{j,t-s}\right] = \sigma^2_{u_i} \; \forall i = j \wedge s = 0, \; 0 \; otherwise.$$

The error term $\chi_{i,t}$ in the local market shock's process is likewise normal, and serially and cross-sectionally uncorrelated:

$$E\left[\chi_{i,t} \chi_{j,t-s}\right] = \sigma^2_{\chi_i} \; \forall i = j \wedge s = 0, \; 0 \; otherwise.$$

The common component's error term ν_t is normal with

$$E\left[\nu_t \nu_{t-s}\right] = \sigma^2_{\nu_t} \; for \; s = 0, \; 0 \; otherwise.$$

The error of the common component ν_t is uncorrelated with the error of the local component $\chi_{i,t}$:

$$E\left[\chi_{i,t} \nu_{t-s}\right] = 0 \, \forall \, i, s.$$

5.4.4 Multiple Common Components

So far I have explained the estimation of only one common price component. If this represents comovement of all prices in the sample this can be referred to as the world component. Each local price series is thus explained by its comovement with the world price and local shocks. However, additional shocks may arise from the national level. Those shocks may be different from global shocks, for example if there are strong border effects that do not allow the transmission of national demand shocks to other countries. In the framework proposed here it is possible to estimate both global and national common components in one model and assess their relative explanatory power. Essentially, the world component explains the variance in all price series and therefore its corresponding weights are all nonzero, while the national components explain only the variance of some price series identified by nationality. For example, the national component of Spain is identified by setting all weights that belong to cities outside Spain to zero. Identifying national components *ex ante* is opposed to obtaining multiple orthogonal common components endogenously and identifying them *ex post*. It implies that the national common components do not need to be orthogonal to each other. What is orthogonal, however, is each national component relative to the world component.

In this setup, Equation 5.2 can be formulated as:

$$P_t = \Lambda C_t + U_t, \tag{5.5}$$

where P_t is an $N \times 1$ vector of N price series, C_t is a $(K+1) \times 1$ vector of common components (the number of a column of ones plus common components), Λ is a $N \times (K+1)$ matrix of weights and U_t is a $N \times 1$ vector of idiosyncratic components. In the case of an international and several national common components, there is one international common component, and $R < N$ national components, with R being the number of countries in the model. For example, in the case of $N = 10$ markets and $R = 2$ countries, each being represented by half of the sample, $K = 1 + R = 3$. The $10 \times (K+1)$ matrix Λ_t contains a column of constants, one column of N elements for the world component and then R columns of weights for each country, which are only nonzero for the observations for the respective country.

Equation 5.5 for this case could then be formulated as:

$$P_t = A + \lambda^w c_t^w + \lambda^1 c_t^1 + \lambda^2 c_t^2 + U_t, \tag{5.6}$$

where P_t consists of 10 price observations in period t, $A = [a_1, a_2, \ldots, a_{10}]'$ is a vector of constants, $\lambda^w = [\lambda_1^w, \lambda_2^w, \ldots, \lambda_{10}^w]'$ is a vector of weights that are nonzero for all i, c_t^w is the value of the world price component in t, $\lambda^1 = [\lambda_1^1, \lambda_2^1, \ldots, \lambda_{10}^1]'$ is the national component for country 1, where only those λ_i^1 are nonzero that correspond to cities of country 1. All other λ_i^1 are set to zero. Accordingly, the elements contained in λ^2 are only nonzero if corresponding to cities in country 2. U_t is a 10×1 vector and contains price elements not explained by either the world component or the respective national component.

The transposed matrix of weights Λ' then looks like:

$$\begin{array}{l} \\ \textit{world component} \\ \textit{national component } 1 \\ \textit{national component } 2 \end{array} \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 & a_6 & a_7 & a_8 & a_9 & a_{10} \\ \lambda_1^w & \lambda_2^w & \lambda_3^w & \lambda_4^w & \lambda_5^w & \lambda_6^w & \lambda_7^w & \lambda_8^w & \lambda_9^w & \lambda_{10}^w \\ \lambda_1^1 & \lambda_2^1 & \lambda_3^1 & \lambda_4^1 & \lambda_5^1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda_6^2 & \lambda_7^2 & \lambda_8^2 & \lambda_9^2 & \lambda_{10}^2 \end{bmatrix} = \Lambda'$$

Accordingly, a single price observation $p_{i,t}$ is composed of the following elements:

$$p_{i,t} = a_i + \lambda_i^w c_t^w + \lambda_i^1 c_t^1 + \lambda_i^2 c_t^2 + u_{i,t}, \tag{5.7}$$

where one of the national weights is zero.

I follow Kose et al. [2003] in estimating the multiple common components. They apply a sequence of single common component models. c_t^1 and c_t^2 are estimated for the variance unexplained by c_t^w. The rest of the model is the same as in the single component model above, only that there are $K = 1 + R$ common component AR-processes now:

$$c_t^k = \varphi_1^k c_{t-1}^k + \ldots + \varphi_q^k c_{t-q}^k + v_t^k, \tag{5.8}$$

where $k \in \{w, 1, \ldots, R\}$ and

$$E\left[v_t^k v_{t-s}^j\right] = \sigma_{v^k}^2 \;\forall\, k = j \,\wedge\, s = 0;\; 0 \,\forall\, k, s.$$

5.4.5 Estimation

The classical estimation of a state space system is standard in multivariate time series econometrics [Hamilton, 1994, Stock and Watson, 1990, Geweke, 1977]. However, I follow the Bayesian way of estimation, in part because the dimensionality is much less of a problem as I can use Gibbs sampling that reduces the curse of dimensionality. Another reason is that it is a convenient way to deal with uncertainty about the unit root properties of the variables [Uhlig, 1994].

The single component model is described in detail in Otrok and Whiteman [1998]. In the next subsection I relate mostly to Kose et al. [2003], which features the estimation of K common orthogonal components.

Kose et al. [2003, p. 1220f] explain why Bayesian estimation is convenient for this class of models. The challenging aspect of the estimation is that both a linear regression with serially correlated errors and the AR-coefficients of c_t have to be determined simultaneously. This is done in classical statistics by utilizing the linearity of the model in the observables. A Kalman filter-smoother procedure leads to the unobserved parameters' likelihood function. It is Gaussian and can be estimated by maximum likelihood [Stock and Watson, 1998]. However, if the the model becomes large in the cross-section it is difficult to estimate, since dimensionality increases exponentially [Kose et al., 2003, p. 1220f].

Bayesian methods allow for estimating the common component c_t and the other parameters $(\phi, \theta_i, \sigma_u, etc.)$ of the model separately. In Bayesian statistics the unknowns are treated as random variables, as opposed to in classical statistics where they are treated as constants. Treating the model parameters and the common component as random implies determining their probability distribution. Unfortunately, for the model above, the joint distribution of the parameters and the common price component is nonstandard. This problem can be solved by decomposing the joint distribution of the parameters and the common component into conditional distributions. One is the distribution of the parameters conditional on c_t, and the other is the distribution of c_t conditional on the model parameters. These conditional distributions have standard forms and are therefore computable. Moreover, the optimization problem for the variable specific parameters is done separately for each observable $p_{i,t}$ and does not increase exponentially with the number of variables N, since the covariance matrix of the $u_{i,t}$ is diagonal, i.e., all cross-sectional correlation is contained in the common components [Kose et al., 2003, p. 1220] and not in $u_{i,t}$.

The sampling, i.e., making random draws from posterior distributions derived from the model, is done by a Markov chain Monte Carlo (MCMC) procedure.[6] Upon iterating on sampling, the Markov property of the marginal distributions,

[6]"Monte Carlo," because artificial data are generated, and "Markov chain", because the distribution conditions only on the last iteration and not on the whole history.

which is to converge to an asymptotic distribution, is utilized.

To begin, a vector of arbitrary starting values is chosen for the common component. The distribution of the parameters conditional on that value is then determined and a vector of values for the parameters is sampled, which finishes the first iteration. In the second iteration, a new value for the common component is drawn conditional on the draw for the parameters from the previous iteration. Then, new values for the parameters are sampled conditional on the new common component draw. The procedure is repeated until convergence is achieved. It can be shown that the conditional posterior distributions converge to the true desired marginal posterior distributions as the number of iteration steps goes to infinity [Geman and Geman, 1984] Here the number of draws is 24,000 of which I use 20,000 for inference, and discard the first 4000. The latter is done in case the starting value was chosen inferiorly. As a convergence check, I repeat the procedure several times with different starting values and compare the respective results. The AR-order for the world common components is chosen as $q = 8$, which reflects business cycle frequency with annual data. For the variable specific processes, $p = 3$ is chosen following Kose et al. [2003]. I have estimated several variations of this setup and found that the results are robust to the choice of the AR-orders.

Two approaches are proposed in the literature for sampling the common component conditional on the parameter draw. One is Otrok and Whiteman [1998] and the other Kim and Nelson [1999a]. I have followed the former, having compared the outcomes of both methods. The results are basically the same. In the appendix, Section C.1, I formally describe the sequence of draws.

5.4.6 Identification

The identification issues here have been discussed extensively in Otrok and Whiteman [1998]. The principal problem is that the weights λ_i and the latent variable c_t are determined jointly in Equation 5.2 and the following two cases are observationally equivalent: $\lambda_i c_t$ and $(-\lambda_i)(-c_t)$. This problem can be solved by pinning down one (and only one, since this in turn pins down c_t) λ_i to be positive. In the example chosen above identification is achieved through setting λ_1^w greater than zero, as well as λ_1^1 and λ_6^2, the first national factor loadings in rows 3 and 4, respectively [Kose et al., 2003, p. 1219]. Here I choose the weight corresponding to the price of wheat in London to be positive; i.e., to be positively correlated with the world price, which does not seem to be a very strong restriction. The cities whose prices are assumed to be positively correlated with their respective national common component are Paris for France, Berlin for Germany, Stockholm for Sweden, Vienna for Austria-Hungary, Brussels for Belgium, New York for the U.S., Oslo for Norway, and Santander for Spain.

A similar problem arises if for example c_t is measured in centimeters and λ_i

in inches – or vice versa. The scale of the common component is undetermined, which is due to the fact that the variance of the common components' error term v_t is not identified. Following, among others, Sargent and Sims [1977] it is set to one, but it could be set to any other constant likewise.

5.4.7 Priors

The priors I use are the same as those in Kose et al. [2003, p. 1221]. Five prior distributions must be chosen. The first two are the distributions of the AR-parameters for the common component (Equation 5.8) and the local shocks (Equation 5.3). Next is the prior distribution of the factor loadings λ followed by the prior distributions of the variances of the local shocks' and the common components' error terms, $\sigma^2_{v^k}$. The latter is the easiest, since for identification purposes explained above it must be set to a constant and thus has no distribution (Section 5.4.6).

The variance of the local shock's error term has an inverted gamma prior distribution:

$$\sigma_\chi^{prior} \sim \mathscr{IG}(6, 0.001)$$

which implies a fairly loose prior. Thus I do not claim to have important prior knowledge about the idiosyncratic error variance and leave the setting of its value mostly to the data.

The AR-parameters of both the common component and the local shocks have normally distributed prior distributions with zero mean, implying the assumption that they are not serially correlated. The more distant the lag is, the more certain this assumption becomes, and thus the variance around zero decreases exponentially:

$$\varphi^{prior} \sim \mathscr{N}(0_{q\times 1}, \Sigma)$$

where

$$\Sigma = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{x} \end{bmatrix},$$

with $x = p$ or q.

5.4.8 Presentation of Results

This section explains how the results from the estimation are presented. It especially describes how the variance decomposition is carried out.

In order to capture changes of market integration I choose subperiods. It means that the model is estimated separately for subsequent time periods. In each subperiod, a new world price component and new national price components are derived from the data. Section 5.6 starts with showing the importance of working in subperiods.

I have experimented with different subperiods, and finally decided to choose periods of about 25 years starting from 1806 in order to divide 19th century into even quarters:

1. 1806-1829
2. 1830-1855
3. 1856-1880
4. 1881-1907

This choice is supported by major historical events over these 102 years. The first quarter captures a period of disintegrated world markets, as a result of the Napoleonic Wars and British import tariffs of those years. The next period up to the mid-1850s possibly exhibits increasing market integration as steam ship technology, the railroad and organizational improvements started to proliferate, fewer wars occurred on the European continent, and liberal trade politics became more widespread. The following quarter should continue that development although it includes the American Civil War, which is likely to have had a severe impact on world wheat trade. In the same subperiod, tariffs were reduced due to the treaties induced by Cobden-Chevalier, which however seemed to have little effect on wheat trade [Lampe, 2008]. The last subperiod starting in 1880 is likely to exhibit a strong drive toward Atlantic market integration according to O'Rourke and Williamson [1999]. On the other hand, some countries increased tariffs that had been lowered or abolished earlier in the century.

In order to assess the relative explanatory power of the components for each price series I follow Kose et al. [2003] who employ variance decomposition for each price series i of the form

$$var(p_i) = (\lambda_i^w)^2 var(c^w) + (\lambda_i^1)^2 var(c^1) + (\lambda_i^2)^2 var(c^2) + var(u_i) \tag{5.9}$$

resulting in the fraction of volatility explained by the world component:

$$\frac{(\lambda_i^w)^2 var(c^w)}{var(p_i)}. \tag{5.10}$$

Since sampling from conditional distributions yields sampling error, the orthogonality of the common components is not automatically given, although they are uncorrelated. Thus, at each step of the Markov chain the national components are orthogonalized relative to the world component. Numerically, this does not change the results in any relevant way, but ensures that the volatility shares add up to 1 [Kose et al., 2003, p. 1226]. In order to give valuable insights into the relative explanatory power of each component, I present arithmetic averages of the volatility shares.[7]

5.5 Data

The data set is taken from Jacks [2005], Jörberg [1972, Sweden], and Jacobs and Richter [1935, Germany].[8] I do not use all series, because some start too late or end too early. For several reasons, I work with annual data here: first, it increases data coverage, second, the problem of seasonality does not arise, and third, it is interesting for economic historians if the proposed method is applicable even to low frequency data. The data set with which I work contains 60 annual wheat price series ranging from 1806 to 1907. The Norwegian and the Spanish series as well as the observations for Cincinnati only start in 1830.[9] In the results section, I discuss how I included them in the estimation. Wheat prices are observed in the following markets:

- Austria-Hungary (4): Viensna, Lwow, Krakow, Ljubljana (Krakow did not belong to the Hapsburg monarchy for the whole period)
- Germany (4): Königsberg/Kaliningrad, Hamburg, Berlin, Munich
- Belgium (3): Ghent, Bruges, Brussels
- U.K. (12): London, Manchester, Liverpool, Exeter, Carmarthen, Dover, Gloucester, Worcester, Cambridge, Norwich, Leeds, Newcastle
- France (11): Bayeux, Saint-Brieuc, Toulouse, Bordeaux, Chateauroux, Mende, Barleduc, Arras, Pau, Lyon, Paris

[7] I carried out the same for the standard errors of the decomposed variances, which can be found in the appendix. This was not done at every step of the Markov chain, but still provides a good view of the average accuracy of results of the variance decomposition.

[8] All series are annual or seasonal variations have been controlled for in another appropriate way [Jörberg, 1972].

[9] Earlier prices for Cincinnati exist, and have been used to form wholesale price indexes for the Ohio delta 1816-1860 [Berry, 1935]. Future research will complete the data set using the sources given there.

- U.S. (4): New York, Alexandria, Philadelphia, Cincinnati
- Sweden (11): Stockholm, Uppsala, Södermanland, Östergötland, Kalmar, Halland, Skaraborg, Örebro, Västmanland, Gästrikland, Hälsingland
- Spain (9): Cordoba, Gerona, Granada, Lerida, Oviedo, Segovia, Zaragoza, Santander, Burgos
- Norway (2): Bergen, Christiania/Oslo

Figure 5.2 shows the geographical extent of the European markets in the sample. Figure 5.3 presents the same for the U.S. markets.

Although scattered data exists for Italy, Odessa and more German cities, the coverage is not sufficient. There are 19th century wheat prices from many German cities, but only up to the 1860s [Fremdling and Hohorst, 1979]. Italian data is plentiful, too, but it either starts in the 1860s or ends in 1899. The reason why there is sometimes better data coverage for the first half of the 1900 may be that administrations tried to control prices to preserve domestic peace, but progressing political and economic liberalization led the states to abandon those attempts after the middle of the 19th century.[10]

For the empirical model employed here it is not necessary to convert the coins and weights and volumes as long as they remain constant over time. Unit differences only represent permanently different means that do not affect comovement. The means of all data series are therefore normalized to 0. Similarly, the variance of each series is normalized to 1.

The price data provided by Jacks [2005] is converted to American dollars per 100kg. I ensure that all prices are expressed in gold dollars but not in greenbacks. There are large relative price variations during the 1860s, which make such an exercise advisable. I used gold denominated benchmark price series from independent sources to compare them with the original prices. I also directly look at the relevant exchange rates found in the Global Financial Database. The appendix documents this in detail. I find that Spanish, Austria-Hungarian, and English prices are converted to gold dollars, while the others are provided in greenbacks. As a consequence, instead of recalculating all currency conversions, I continue to work with Jacks' data, deflating the series given in greenbacks such that all series are denominated in gold dollars per 100kg.

Although overall inflation in the 19th century was small, I take out long run trends from the data by applying a Hodrick-Prescott filter with the Ravn-Uhlig lambda of 6.25.[11]

[10] I thank Michael Kopsidis for this remark.

[11] Alternative filters like Baxter-King and Christiano-Fitzgerald yield very similar results [Baxter and King, 1999, Christiano and Fitzgerald, 2003].

Figure 5.2: European markets.

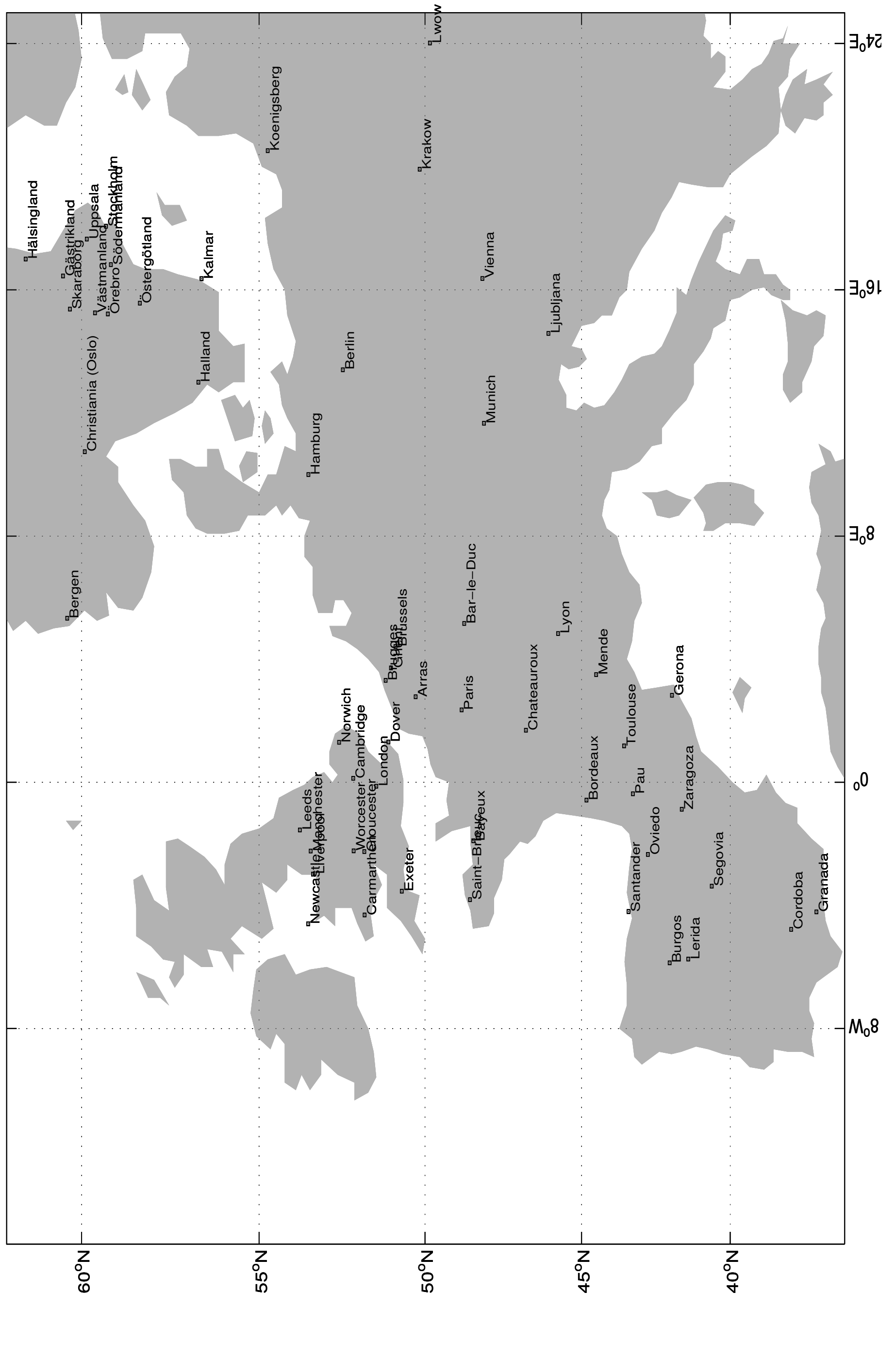
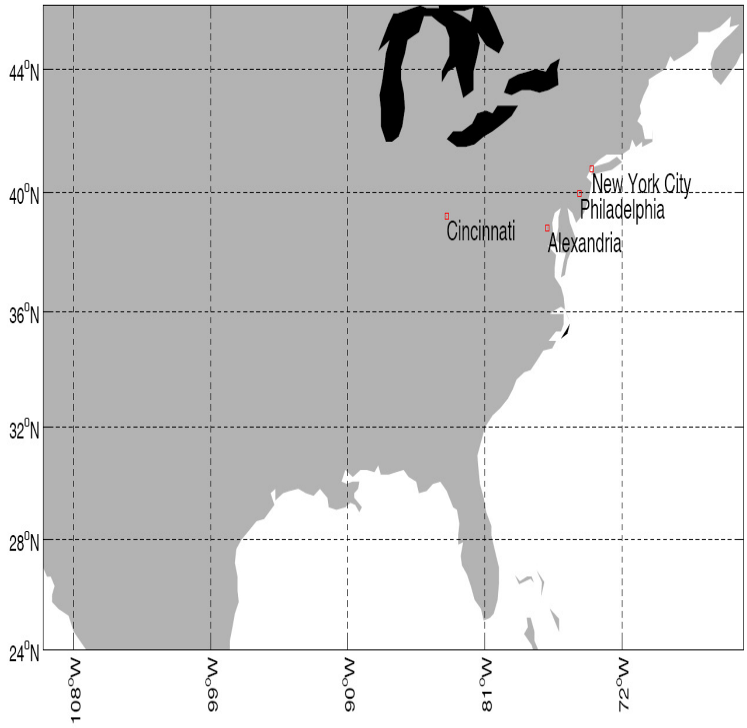


Figure 5.3: American markets.



5.6 Results

5.6.1 Evidence for Structural Change

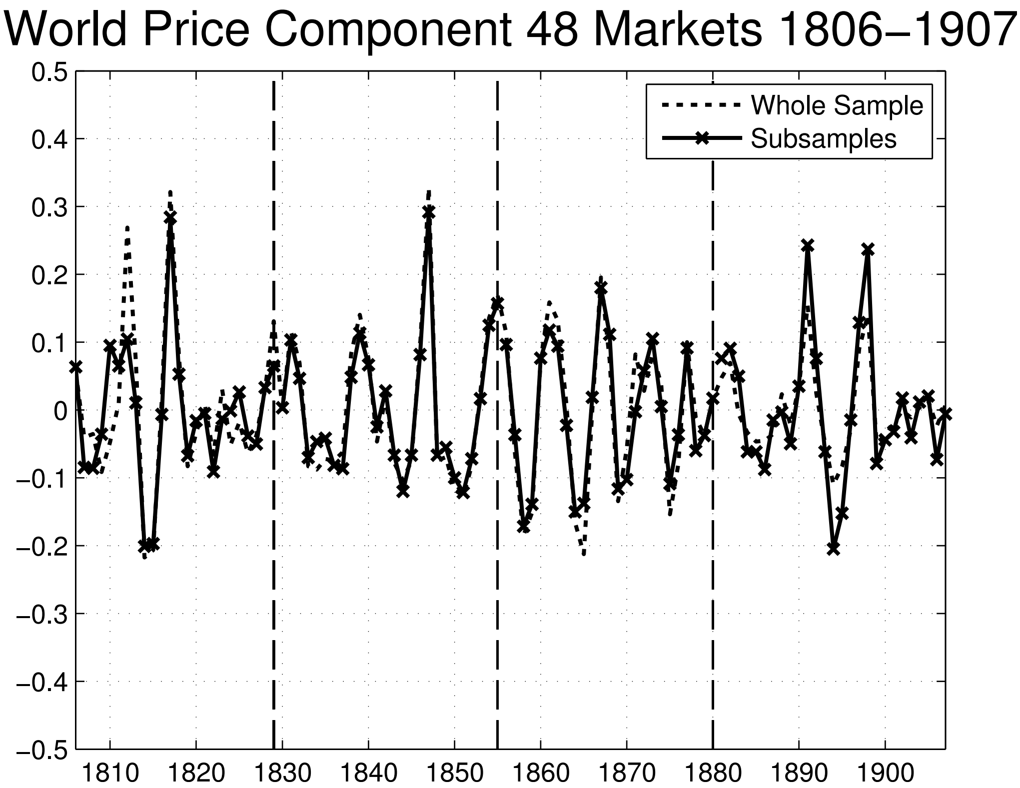
In order to give an impression of the changing comovement in the 19th century Figure 5.4 plots a world price component spanning 102 year from 1806 to 1907 against subperiod world price components, each spanning about 25 years.[12] The standard deviation of all series price components is normalized to 0.1, which is the average standard deviation of English wheat prices in the 19th century. The fluctuations are percentage deviations around a smooth trend as discussed in the data section. The vertical lines divide subperiods.

We can clearly observe the price peak in 1847, which was induced by bad harvests throughout Europe in 1846 [Berger and Spoerer, 2001]. The common component confirms also the notion that wheat did not strongly take part in a worldwide "speculative" inflation of 1870-73 Veblen [1893, p. 20].

If structural change did not matter, estimating the model for the whole period

[12]Kose et al. [2008] estimate a similar model for subperiods in order to capture structural breaks in world business cycle comovement.

Figure 5.4: World price component during 19th century. Whole sample estimate vs subsample estimates.



or breaking it up would make no difference to the common price component. What Figure 5.4 demonstrates instead is that, in three out of four periods, the subsample world price (solid line) is different from the world price estimated from the full sample (dotted line). Before 1830 the subperiod world component does not exhibit the strong peak around 1812 as the full sample component does. Conversely, the M-shaped price deviations centered on 1895 are much stronger when taking only information after 1880 into account. In the 1850s and 1860s, the restricted sample world price fluctuates less than its full sample counterpart.

Apart from misspecification of the common component, taking the period as a whole prohibits the relative weights λ_i to change over time. They represent each market's sensitivity to world price fluctuations. Without breaking the sample up, it would be impossible to capture changes in the degree of how much single markets take part in world wheat trade.

Antebellum International Market Integration

The trend obtained for worldwide comovement is shown in Figure 5.5 as a cross country average. It reveals the integrating forces of world trade in the 19th century. Globalization according to Figure 5.5 manifested itself in a strong increase between the first and the second quarter of the 19th century: the world component explains on average only 34% price variance between 1806 and 1829, but 58% between 1830 and 1855. This first shift to integrated markets is followed by a second, albeit smaller one, as the flatter shape of the upper curve in Figure 5.5 shows. At the same time national market integration, representing solely national comovement, steadily declined in the 1800s, first quickly, then at a slower pace. These two developments add up to decreasing market separation; i.e., on average 19% of price variance was subject to local shocks before 1830, compared to only 8% after 1880 (not shown).

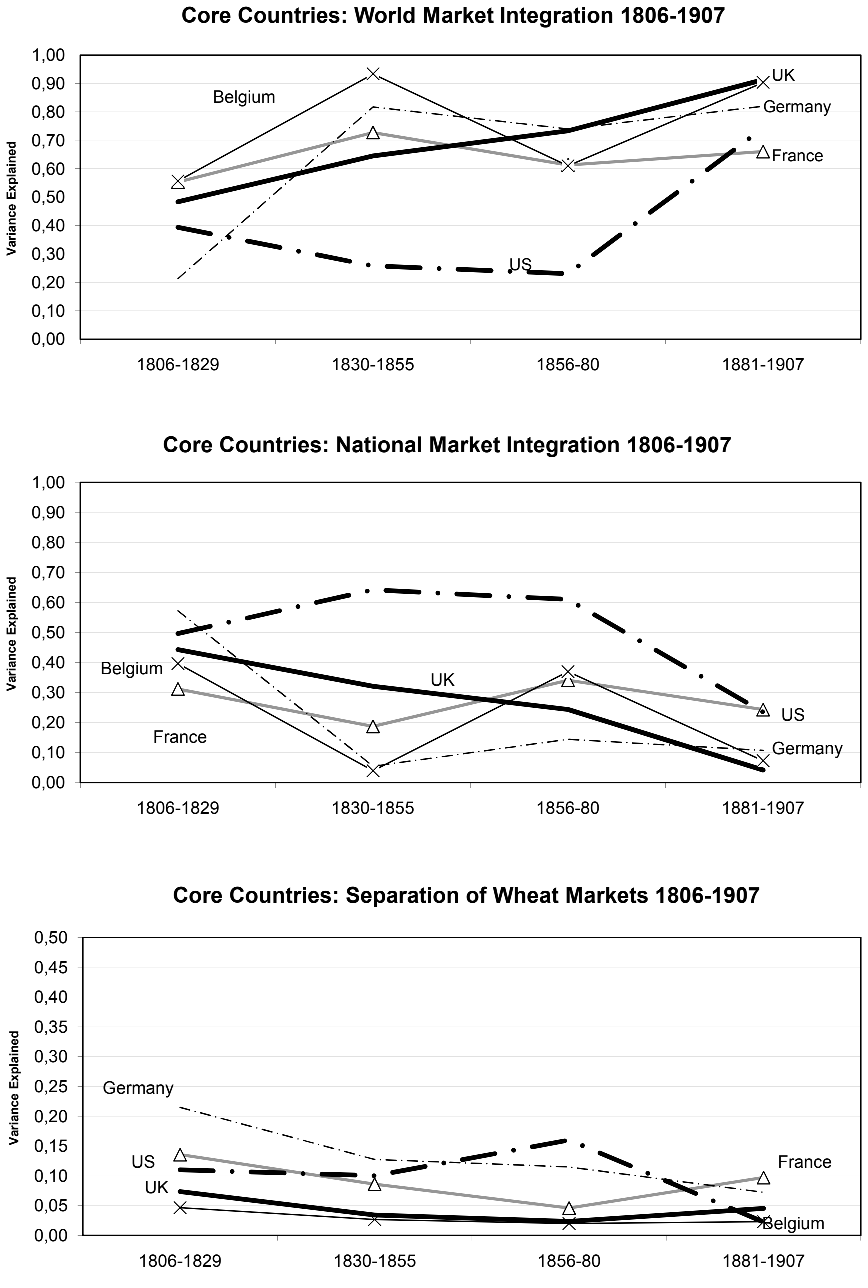
These results emphasize the role of market integration in the first half of the 19th century, as opposed to the "First Wave of Globalization" story famously put forward by O'Rourke [1997], among others. Recently there has been greater recognition of the former point, the post-Napoleonic improvement of world commodity market integration. Jacks [2005] finds decreasing transport costs for wheat before 1860 and Federico [2008] reports declining price dispersion in European wheat prices from the early 1800s on. Kaukiainen [2001] proposes decreasing information costs on why markets could come to function so much better without the widespread use of steam technology and the telegraph. He finds that business letters to and from London traveled on average twice as fast in the middle of the 19th century than at the beginning. Factual transport cost in sail shipping decreased impressively, as Brautaset and Grafe [2005] find. They argue that economies of scale can explain these cost reductions in shipping.

5.6.2 Broad Trends

The country averages are presented in Figures 5.6-5.7. Figure 5.6 contains averages for the major countries such as the U.K., the U.S., France, Austria-Hungary and Germany, while Figure 5.7 features Norway, Sweden, Belgium and Spain.[13] The upper panel shows world market integration, the middle national market integration and the lower one market separation in the sense that it shows the share of price variance, which is explained by neither national nor international comovement. The results are presented in such a fashion that it is possible to get a complete picture of a country's market integration process throughout the 19th century.

[13] The full set of results can be found in the appendix.

Figure 5.5: Development of world and national market integration, 1806-1907. Averages over cities' variances explained by world and national price component.



In the U.K. for example, the upper part of Figure 5.6 shows that it continuously integrated into the world market. At the same time the middle panel shows that conditional on world market integration the importance of national specific

Figure 5.6: Development of world, national and local component, core countries, 1806-1907. Country averages.

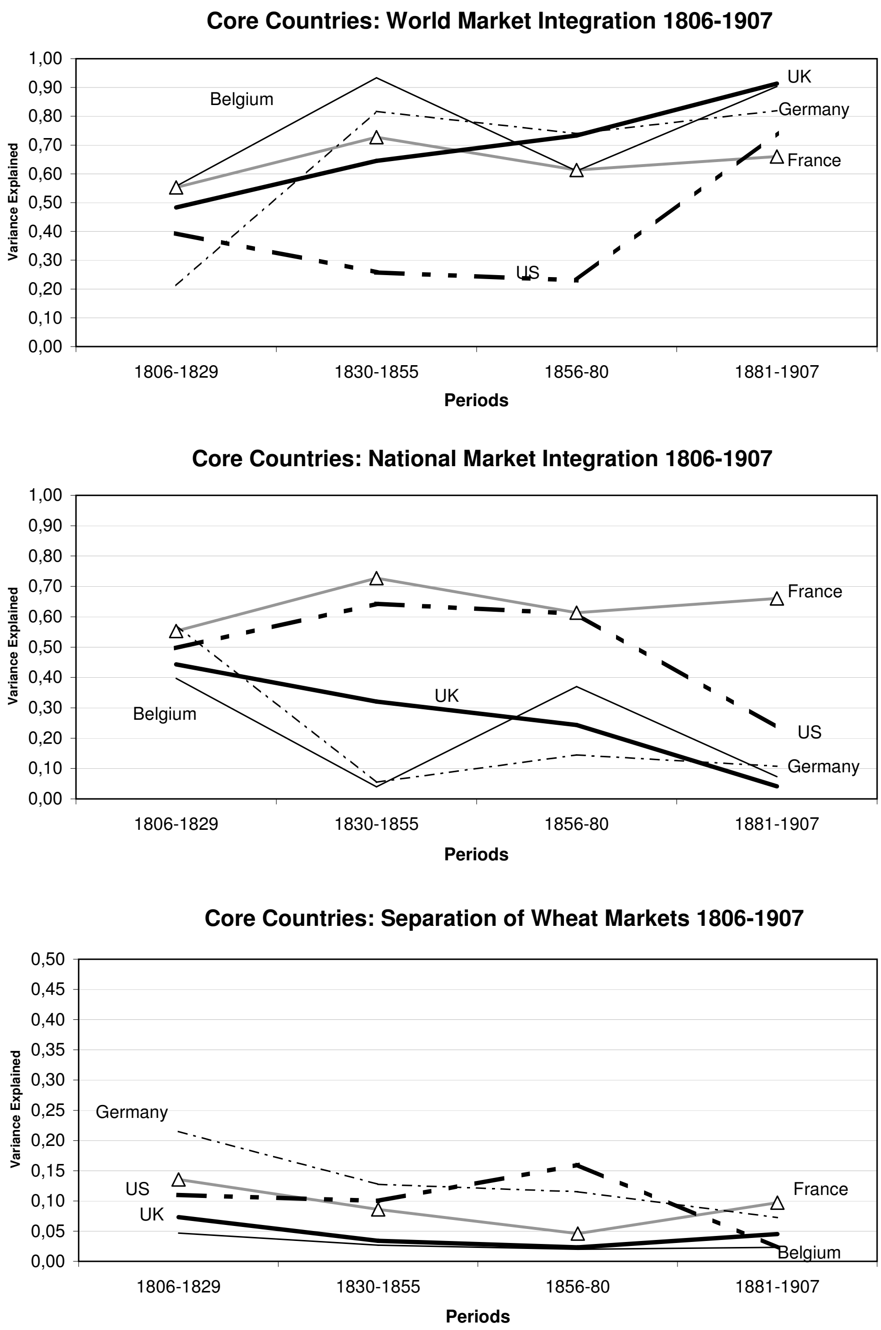
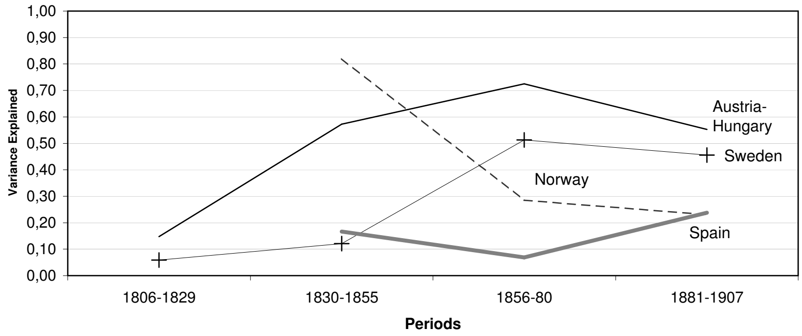
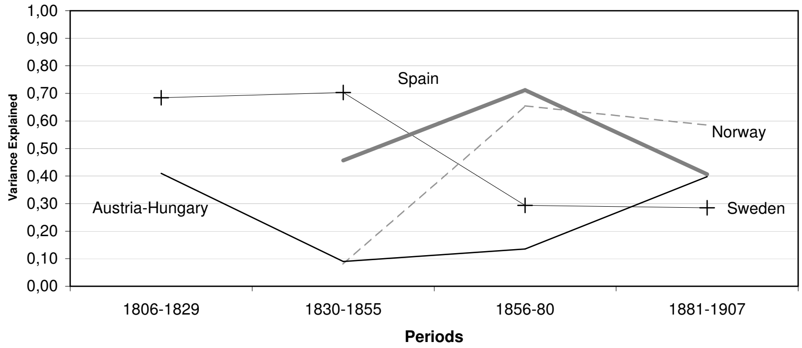


Figure 5.7: Development of world, national and local component, periphery countries, 1806-1907. Country averages.

Periphery Countries: World Market Integration 1806-1907



Periphery Countries: National Market Integration 1806-1907



Periphery Countries: Separation of Wheat Markets 1806-1907

shocks decreased continuously. The lower panel shows a very low value of separation. Thus already in the beginning of the 19th century, U.K. markets were either nationally or internationally integrated with local shocks having almost no influence on local prices at all.

Three new perspectives on 19th century wheat market integration can be deduced from these results. First, European market integration before 1860 has been neglected in the literature relative to transatlantic market integration. The European market is not the consequence of a return to protectionism under Bismarck & Co in the 1880s but a result of weakening market forces after the end of the Napoleonic Wars. Second, the American Civil War represents a phase of transatlantic market disintegration; therefore postbellum market integration is a candidate for a postwar reconstruction phenomenon. This puts the "Grain Invasion" into perspective. The third result relates to the relative development of national and international integration, which was different across countries.

U.S. Accession to European Integration Levels

These results imply that the story to be highlighted in 19th century international wheat market integration is maybe not so much one of America and Europe merging into a common transatlantic market due to reduced transport costs, but rather that of an already integrated European market that opened up to another major supplier. One could also argue that it is likely that the strong increase in comovement between American markets with the world price could have occurred one or two decades earlier but was impeded by the Civil War (see Sharp [2008] for a similar argument). The level of integration of the U.S. markets at the end of the century, however, is comparable to that of France's as the top panel of Figure 5.6 shows. While the U.K.'s markets are integrated best in the last quarter of the 19th century, major German cities come second, well above the U.S. markets. If the U.S. markets are placed between France and Germany, two protectionist countries in terms of market integration, then a changed perspective relative to the traditional story of protectionist and free market nations after 1880 seems to be justifiable (see O'Rourke and Williamson [1999] for the established view).

Late National Market Integration and Urban Demand for Wheat

The third set of results stems from the ability of the model to truly differentiate between national and international integration. They evolve differently across nations in the 19th century as the middle panel in Figure 5.6 shows. While toward the end of the 19th century we observe decreasing sensitivity to national shocks in the U.K., the U.S. and Germany, in France and especially in Austria-Hungary national shocks explain more than they do in the preceding subperiod (Figure

5.7). A related pattern can be observed in Spain, where national shocks' explanatory power decreases but remains on a very high level. On average wheat prices in Spain are explained 50% by national shocks, and about 35% by local shocks (Figure 5.14).

While protectionism seems to be the first possible explanation for increasing shares of the national component after 1880, another important factor may have been differences in the timing of industrialization across the nations discussed here. Kopsidis [1998, 2002] argues that integration of agricultural markets may have been spurred by industrialization. The creation of urban demand for agricultural goods led to regional specialization, which made it profitable for farmers to produce for the market and ship their goods to the cities. Even in the absence of technological progress unit transport costs may fall during this process due to economies of scale in market efficiency.

5.6.3 Country Results

The **U.K.** is certainly the country of which the highest world market integration and lowest separation of markets can be expected. Easy access to most U.K. cities by waterways and early commercialization are some of the often cited reasons for why industrialization first developed in England. Shiue and Keller [2007] for example find that at the beginning of the 1800s the U.K. was much better integrated than Western Europe on average. One still has to bear in mind that the first few decades witnessed the Napoleonic Wars and the Corn Laws that had an insulating effect on the U.K. wheat markets [Sharp, 2006]. Thus, one may find some limited world market integration and very low local market separation before 1830. Figure 5.8 shows exactly this. Note that there were some differences in the degree to which markets were globally integrated. 76% of wheat prices in Exeter were already determined by the world market, while prices in all other cities stayed below 60%.[14] In the aftermath, all cities converged to the same path of world market integration with shrinking nationally specific price components. Together with Belgium the U.K. emerged clearly as the most integrated wheat market during the second half of the 19th century.

In comparison, **France's** markets experienced a rather marginal development with considerable local heterogeneity. While early in the 1800s cities such as Paris, Lyon and Arras were better integrated into the world market than most U.K. cities, after the 1850s there was rather an anti-global tendency in those cities (Figure 5.9, upper panel). The French average for world integration did not decrease, however, because Toulouse, Mende and Pau followed a path of increasing

[14] In the case of the U.K., France, Spain and Sweden, I did not plot all results to keep the graphs straightforward. All results can be found in the appendix.

integration. France ended the early 1900s as an intermediately globally integrated country with the largest national specific component in the sample (Figure 5.6).

The figures showing market integration in **Belgium** speak very much for themselves (Figure 5.10). All three markets behave almost identically. The largest part of price variation is subject to worldwide shocks (upper panel). The only peculiarity is the swing with a short setback to national specific price variation during the third quarter of the 19th century (upper and middle panel). It is striking that the Belgian markets in the sample were always fully insured against locally specific price shocks, reflected in the extremely low level of separation of all three markets over all periods (lower panel).

The disaggregated view allows for detailed insights into the development of **German** market integration. The upper panel of Figure 5.11 describes the astonishingly strong international integration of the German wheat markets. A global focus arose in the second quarter of the 19th century, too early to be fully explained by railroad or telegraph. It seems plausible to cite the German tariff union as the main driver of market integration. But this would imply strong explanatory power of the national component after 1830, and an increase relative to the first quarter (middle panel). Unfortunately, the small set of markets presented here is not suitable to confirm or refute this hypothesis, because Hamburg never became part of the tariff union, while Königsberg and Berlin have never been divided by tariff boarders. However, it is still interesting to find an already well integrated national market *before* the tariff union ever existed. Similar results were also found by Fremdling and Hohorst [1979] and Shiue [2005].[15] The evidence rather fits into a picture of increasing Baltic and North Sea trade that included the major Prussian and former Hanseatic cities. The introduction of the railroad was not without effect, though. It became important where waterways were missing: Munich, not connected to the Rhine-Weser-Elbe water network, has not been well integrated into the North-German market, as can be seen in the lower panel. Its separation from the North-German market was attenuated probably with the help of the railroad in last quarter of the 19th century.

The **United States** is the only major nation that developed no strong connections with the world market before 1880. Although the U.S. already supplied about half of the U.K.'s wheat imports in the 1850s [Sharp, 2006], they were apparently not well integrated in the world market. What matured earlier, however, was a national market. Between the first and the third quarter of the 19th century comovement between the three East Coast cities New York, Philadelphia and Alexandria increased to such an extent that 60-70% of the variance of their prices was explained by the national component (middle panel in Figure 5.12).

The reason why comovement was strong but distinct from the world business

[15] See Dumke [1991] for details on the German tariff union.

cycle in the third quarter must be the Civil War in the 1860s, accompanied by harvest failures in the U.K. and Europe [Fite, 1906, p. 264]. Agricultural production in the American Midwest during the first Civil War years soared dramatically due to the increase in acreage and harvest luck. At the same time, the river connections to the South were partially closed and the relatively new railroad to Chicago could not meet demand. Thus, transport costs peaked at the beginning of the war, creating a price wedge between the coast and the interior [Fite, 1906, p. 270]. This may explain the strong separation of the wheat market in Cincinnati from the East Coast markets as shown in the lower panel of Figure 5.12 panel and the corresponding decline of Cincinnati's national integration during the third quarter of the 19th century.[16] After the Civil War, internal and external trade flourished: all four markets integrated into the world market to a very high degree (72%).

The case of **Austria-Hungary** seems to be a good example in different evolving patterns of prices in cities within one nation. Before mid-century the eastern markets of Lwow and Krakow were separated from both national and international markets, while Ljubljana and Vienna were better connected to the international market. This seems plausible as they were closer to the rest of the European markets (see the map in Section 5.5). With progressing industrialization, the Hungarian part of the monarchy became the major grain supplier of the Austrian cities, and the national market increasingly integrated. Consequently, the degree to which the now-industrialized urban centers integrated into international market declined, as is shown in Figure 5.13 (see also Komlos [1979]). To sum up, market separation decreases (Figure 5.7, lower panel).

The **Spanish** national market was comparatively underdeveloped, as can be seen in Figure 5.14.[17] It is especially striking that there was no clear direction of development at all. Cordoba and Oviedo, for example, experienced international disintegration and then a thrust to more international comovement in the last quarter before World War I, while Lerida's path of development was the opposite. Overall, Spanish speed of world integration is the lowest in my sample for most of the observation period. Jacks [2005, p. 397] reports similar results from a TAR model. Pena and Albornoz [1984, p. 371] find underdeveloped intraregional wheat markets despite the import prohibition instituted in 1820. According to them, the situation was alleviated only in the 1880s when the railway network was improved. Some of their results can be found here, but still I rather find a sec-

[16] Fishlow [1964] points out that Cincinnati was not a "leading Southern forwarder" (p. 358) and that the share of flour flowing east- and northwards increased from 3 to 90% between 1850 and 1860. But Cincinnati may have been dependent on sending its produce to the North by train or to the South by river – its location between the two fighting parties made its business vulnerable to war interruptions.

[17] Not all results are plotted in order to keep the plot straightforward. The remaining results are reported in the appendix.

ular decline than an improvement in efficiency. Herranz-Loncán [2007] finds both technological and institutional reasons for the relatively large regional divergence in economic development in Spain, confirming the overall low level of market development as I find. Barquín Gil [1997] does claim the existence of efficient commodity markets before 1850, but his sample is restricted to only one southern Spanish city, as Rosés [2003, 1000] criticizes.

When observing the average level of separation of the **Swedish** markets (lower panel in Figure 5.15), one could be tempted to group them into the same category as Spain's. However, there are differences in both development over time and the degree of similarity between the markets.

While the Spanish markets do not show any clear trend, there is an obvious tendency in Sweden toward more market integration, which becomes visible in the top panel of Figure 5.15.[18] Moreover, only a small number of markets such as Uppsala and Hälsingland do not join into world market integration as much as most other Swedish cities. The high level of national market integration in the first quarter of the observation period is remarkable. Considering the Austria-Hungarian national wheat market for example, most cities' price comovements are comparable to Vienna's and Ljubljana's, while none are so asynchronous as Lwow's or Krakow's. In contrast to Spain, almost all Swedish cities are better integrated between 1806 and 1829 than any Spanish market in the following 26 years. The level of national specific shocks falls continuously in almost all Swedish cities, where the period of fastest fall is between the second and the third quarter of the 19th century. This seems rather late compared to other European nations such as Germany, Austria-Hungary and Belgium.

Commenting on **Norway**, the results in Figure 5.16 seem to be counterintuitive. The results show a *decreasing* integration into the world market accompanied by an *increasing* weight of the national component and a U-shaped separation of the markets. The local price component stays always well below 25%. However, I doubt if the model should be set up along national boundaries in the case of Norway. First, only two markets are included as the Norwegian sample, which are separated by mountains, and a train connection was not finished before 1909. In fact, there is no reason whatsoever to assume that Bergen and Oslo, then Christiania, should be part of the same market: until 1905, Norway was not yet an independent nation, and administration functions were to a large part based in Stockholm. Culturally, especially linguistically, the dialect spoken in Bergen was probably related to Oslo dialect no more closely than to what was spoken in Stockholm.[19] Perhaps it would be safer to group Bergen with German or English

[18] Some markets have not been plotted, but the results can be found in the appendix.

[19] Even today there are two kinds of high Norwegian, and many Norwegians speak their local dialect.

markets, and Oslo with the Swedish, which remains to be part of future refinements of this project. The oddness of my results is reflected in Jacks [2005, p. 390, 396], who finds high speeds of international and intranational price adjustment before 1850, which abruptly decrease thereafter.

Overall, the picture drawn here is one showing a stronger wave of globalization in the first half of the century than in the second. The Napoleonic Wars may have suppressed possible trade relations that soon blossomed as the war was over (Federico [2008] follows this track). When dating the start of globalization, certainly we should look somewhere before 1850 similar to O'Rourke and Williamson [2002]. The slowdown of the speed of globalization in the second half of the century should be emphasized. Railroad, telegraph and steamship were not the only forces of world and national wheat market integration. A better explanation should include the impact of wars (or better their absence), gradual technological improvements and the market creating forces of regional specialization in connection with economies of scale in market efficiency.

5.7 Conclusion

In this chapter, I evaluate comovement among wheat prices in different localities to investigate 19th century market integration. Each price is divided into a world, a national, and a local component in four independent subperiods representing stages of market development. The explanatory power of the common components is used to assess changing degrees of market integration over time.

I explain that there was a tendency toward closer integration over the 19th century, but stronger in the first half than in the second. A high degree of international wheat market integration was reached before the telegraph, steamship and railroads could reach their full cost saving potential.

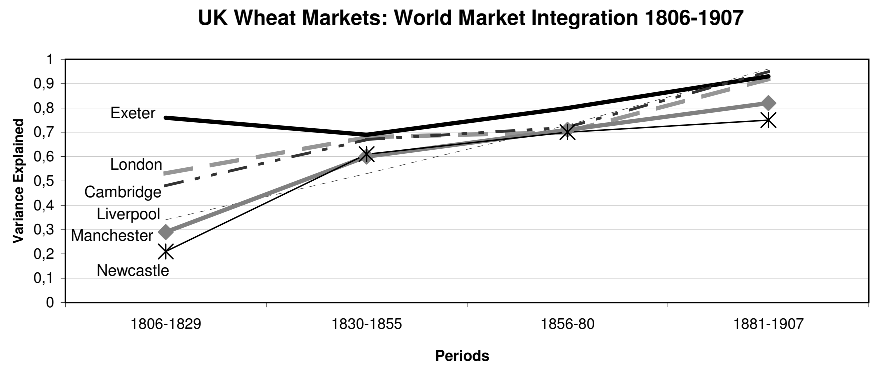
The 1860s was a decade of slower or no improvements of market integration, even when I control for exchange rate fluctuations caused by the decoupling of the paper dollar from gold. The American Civil War was the most likely reason, as it hampered intra-U.S. and Atlantic trade, while the Cobden-Chevalier network had no impact on wheat trade.

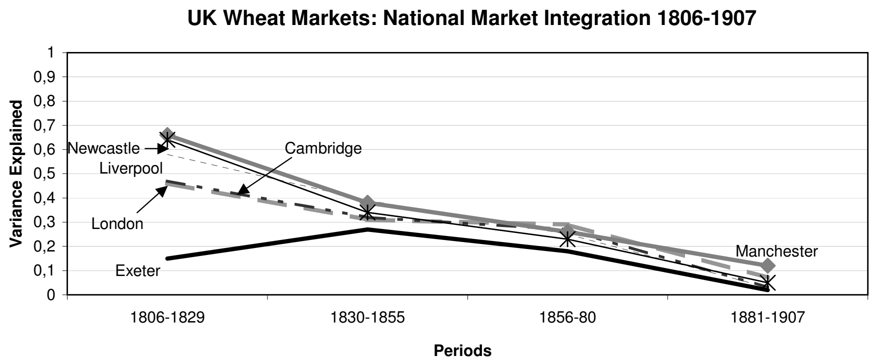
The U.S. markets were only fully integrated into the world market after the Civil War. Even then, they did not set the tone, but rather played one of many fiddles.

The North-German markets became integrated before 1830, while Munich was separated until after the German Reich was founded and railroad connections were established.

The introduction of comovement into the market integration literature has the advantage of forming a benchmark against which each market price can be assessed. Thus, it is not dependent on a battery of bilateral comparisons. Large amounts of price data can be processed and transformed into an intuitive measure of integration. The possibility for looking at each market individually is maybe the strongest argument for this method. Zooming into local circumstances while keeping an eye on the aggregate picture can be accomplished easily. Therefore, this method appears to be a useful means to throw light on questions of market integration in other regions and periods.

Figure 5.8: Development of world, national and local component in England, 1806-1907.





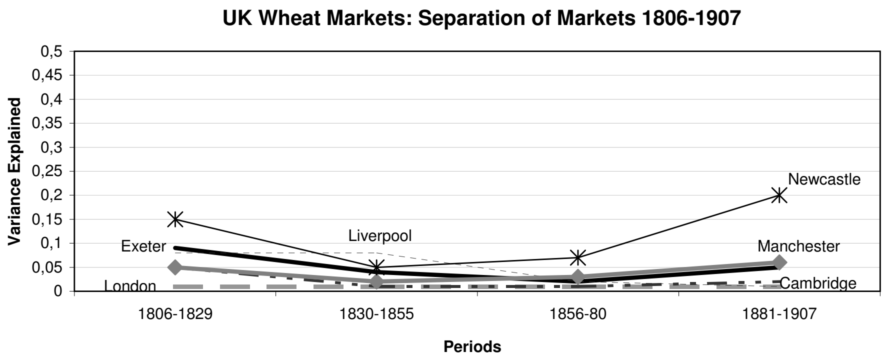
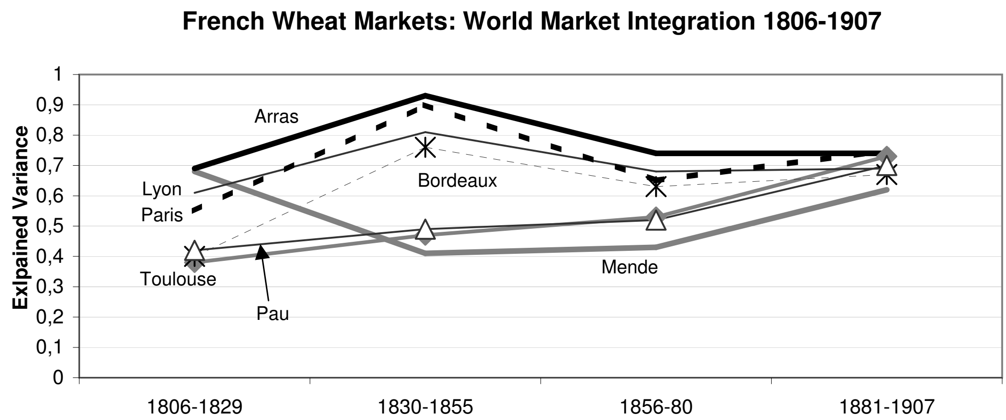
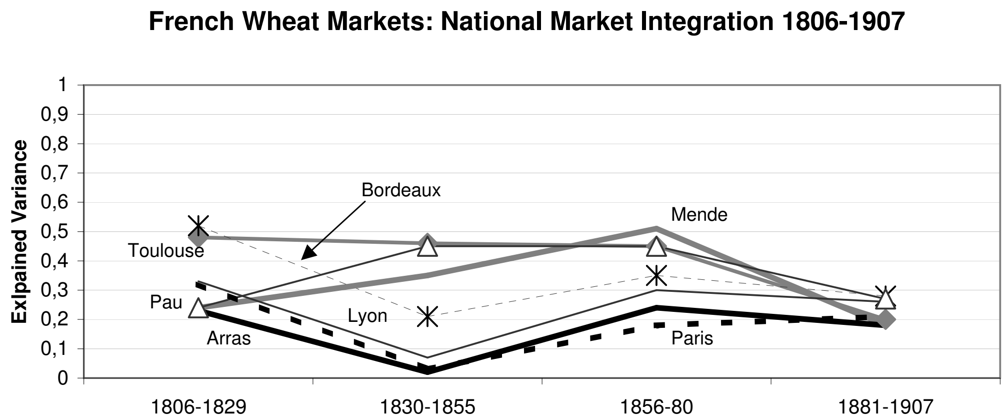


Figure 5.9: Development of world, national and local component in France, 1806-1907.





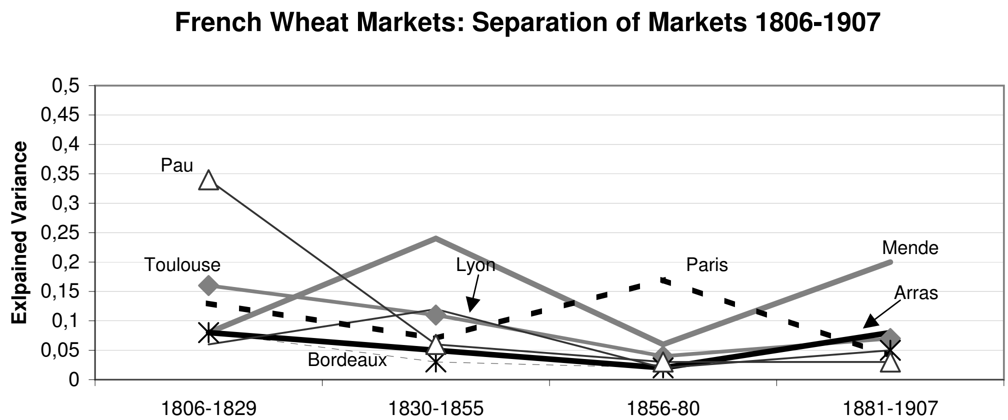
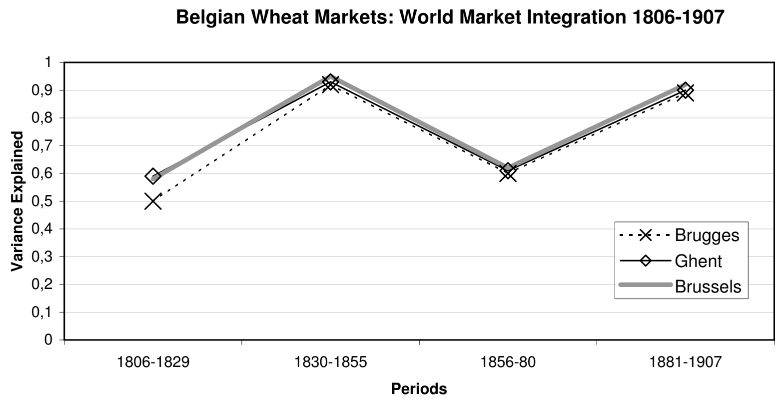
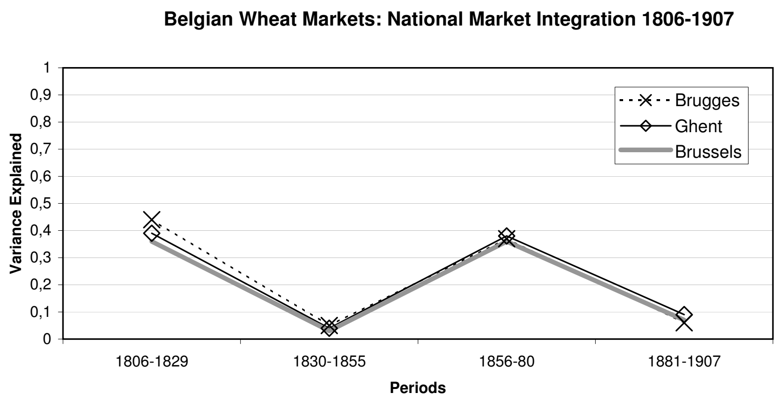


Figure 5.10: Development of world, national and local component in Belgium, 1806-1907.





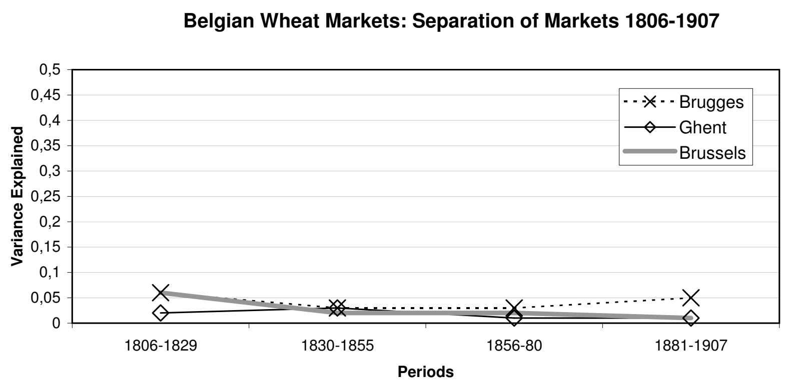
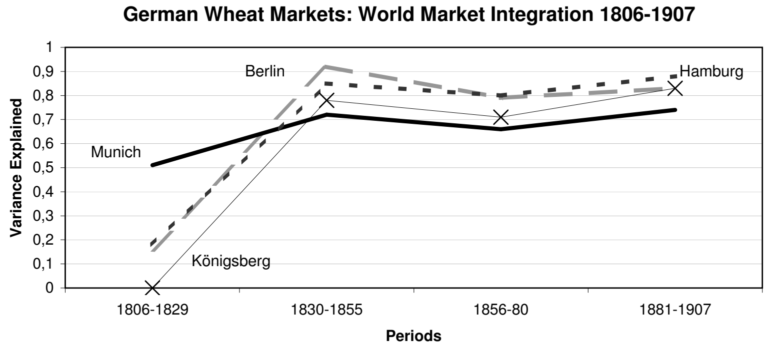
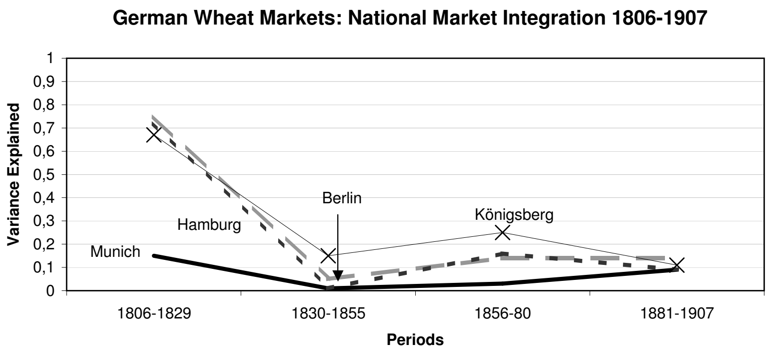


Figure 5.11: Development of world, national and local component in Germany, 1806-1907.





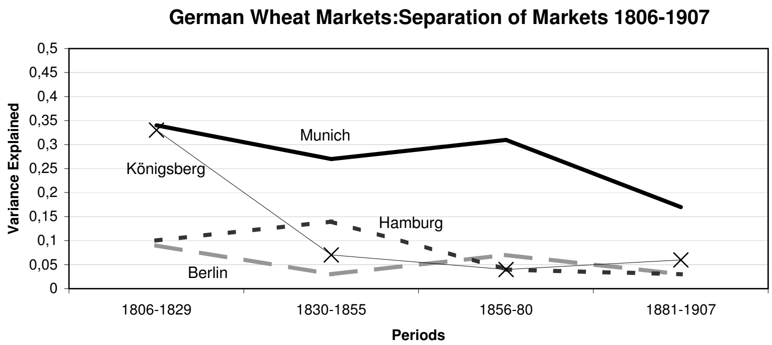


Figure 5.12: Development of world, national and local component in the U.S., 1806-1907.

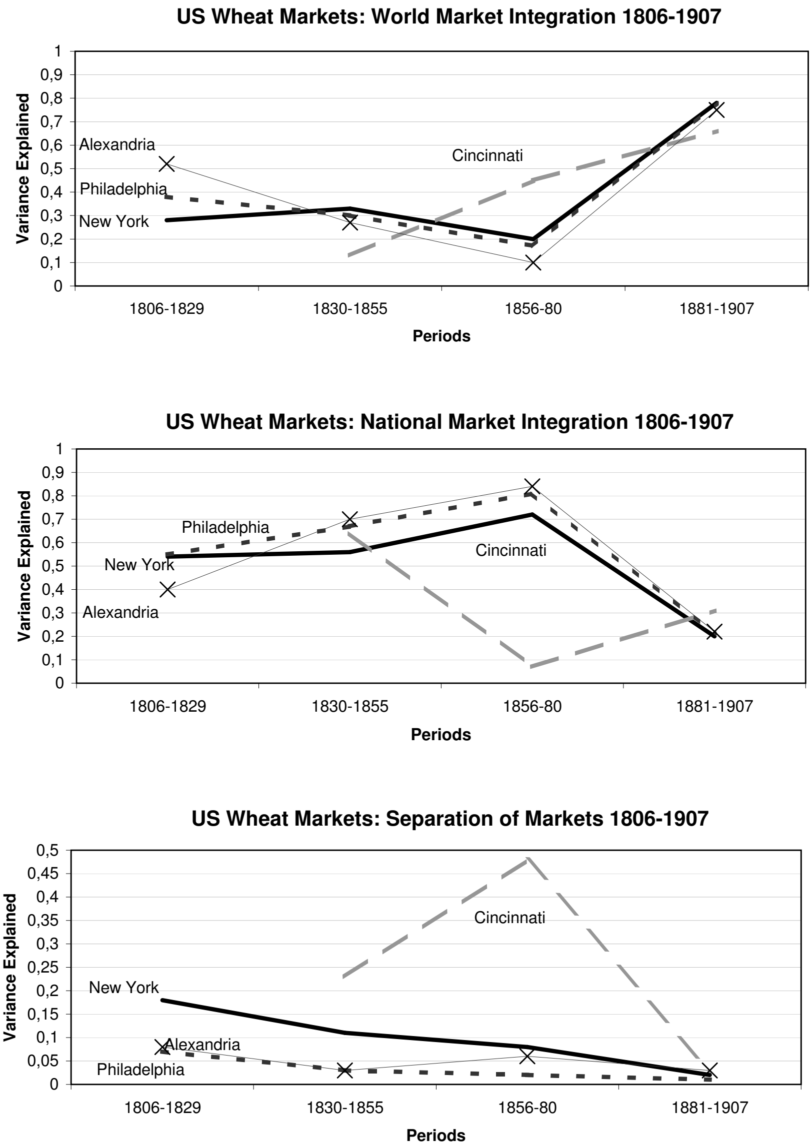


Figure 5.13: Development of world, national and local component in Austria-Hungary, 1806-1907.

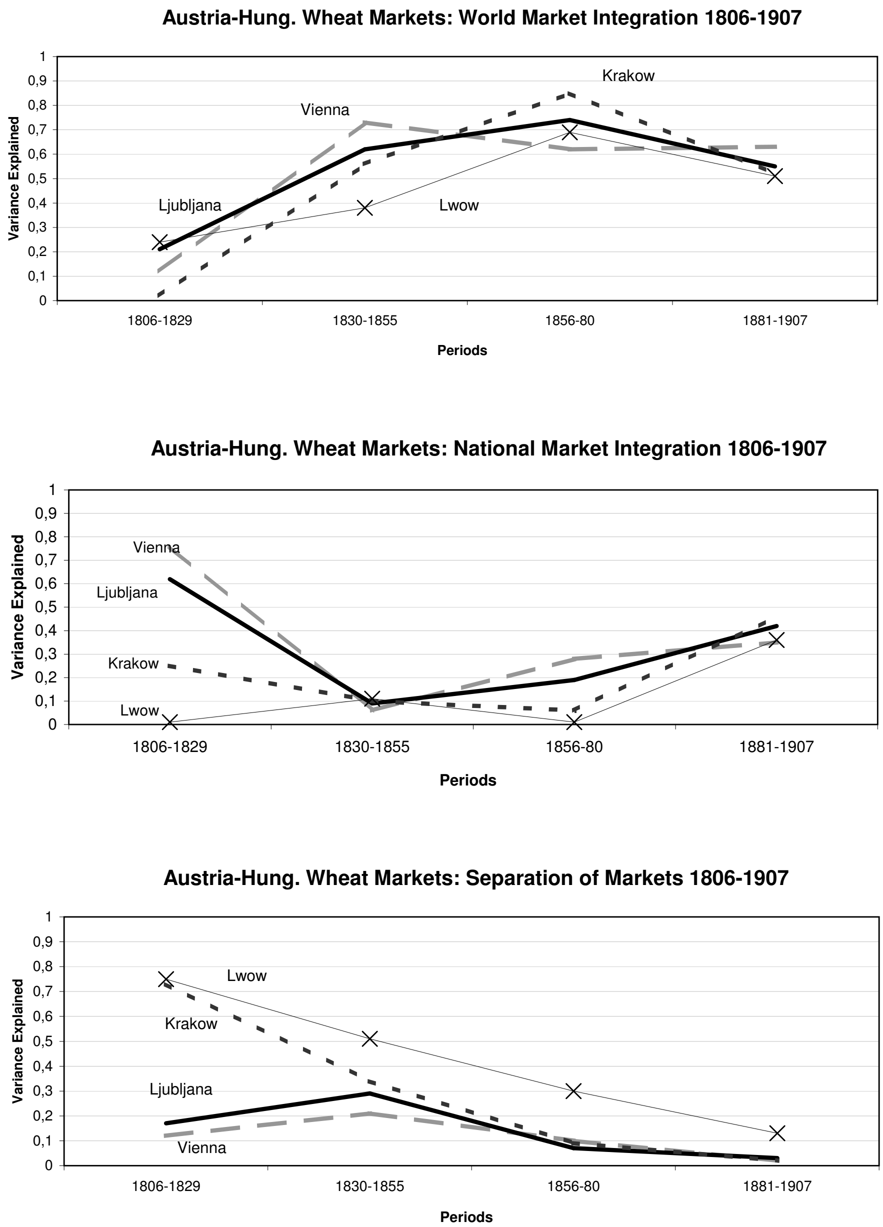
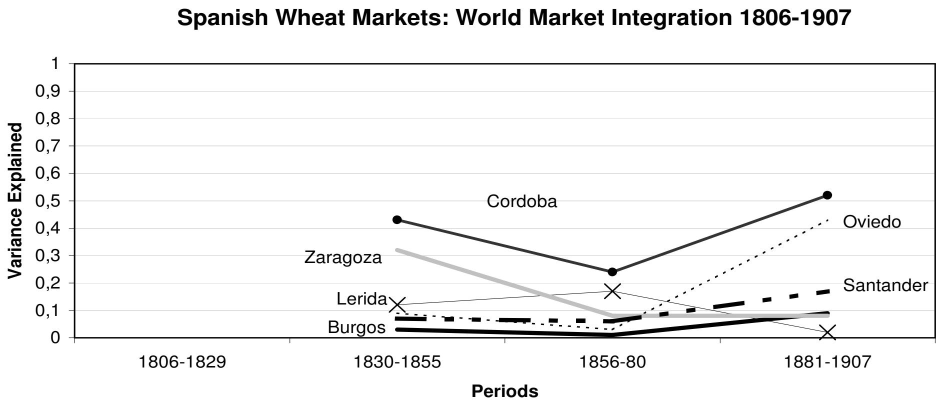
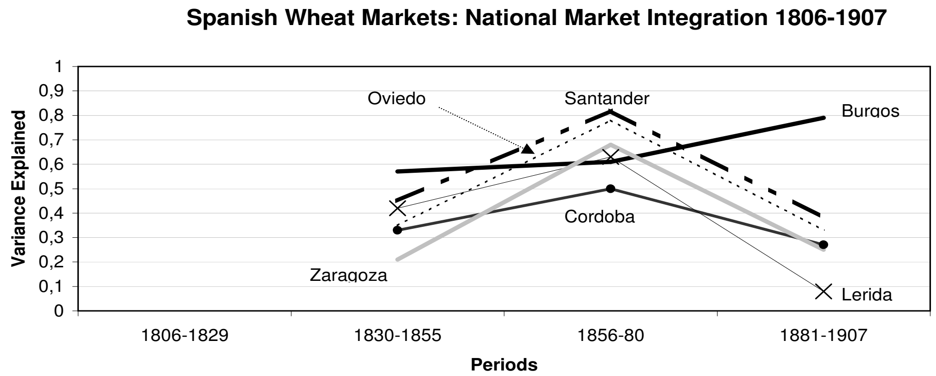


Figure 5.14: Development of world, national and local component in Spain, 1806-1907.





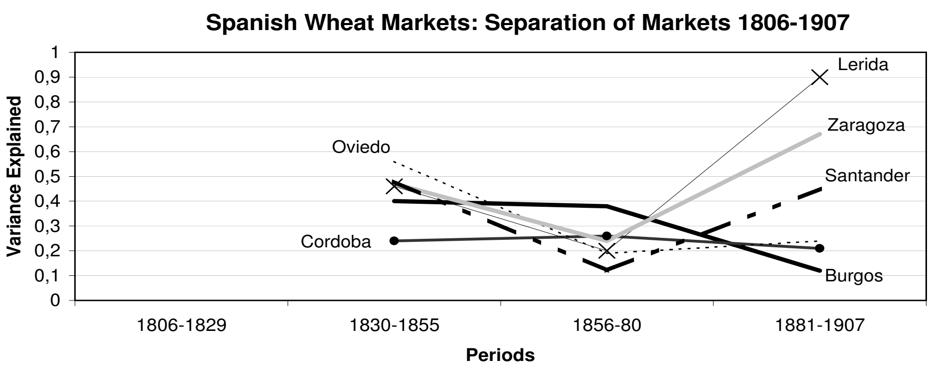
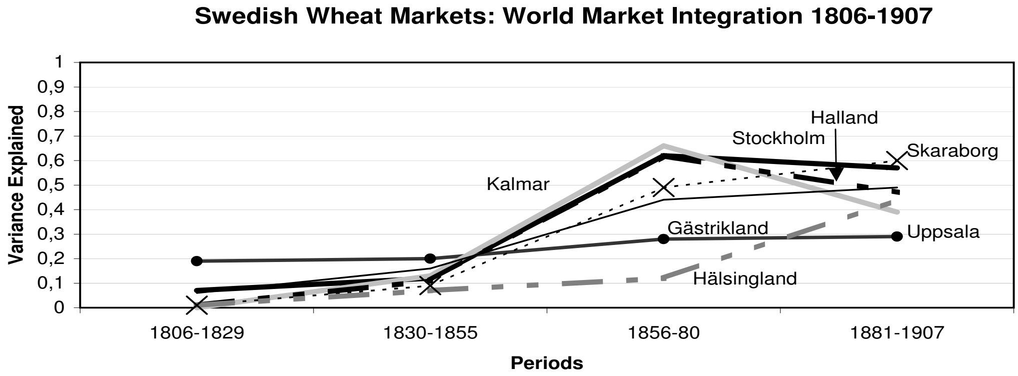
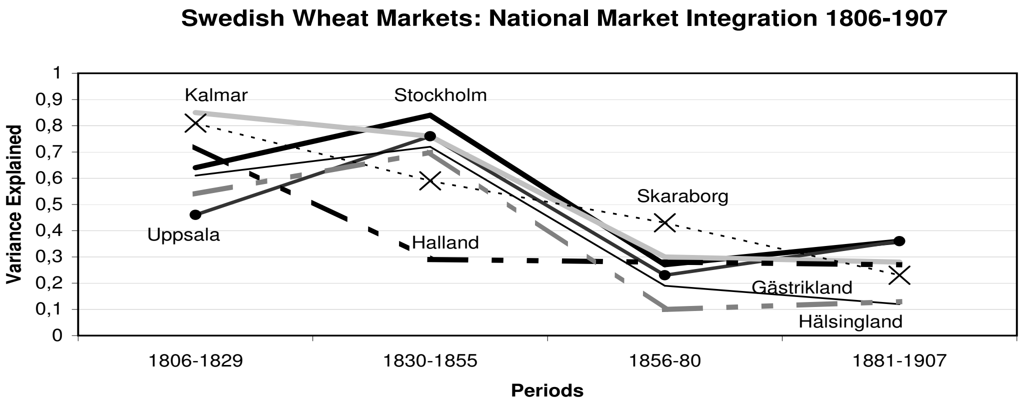


Figure 5.15: Development of world, national and local component in Sweden, 1806-1907.





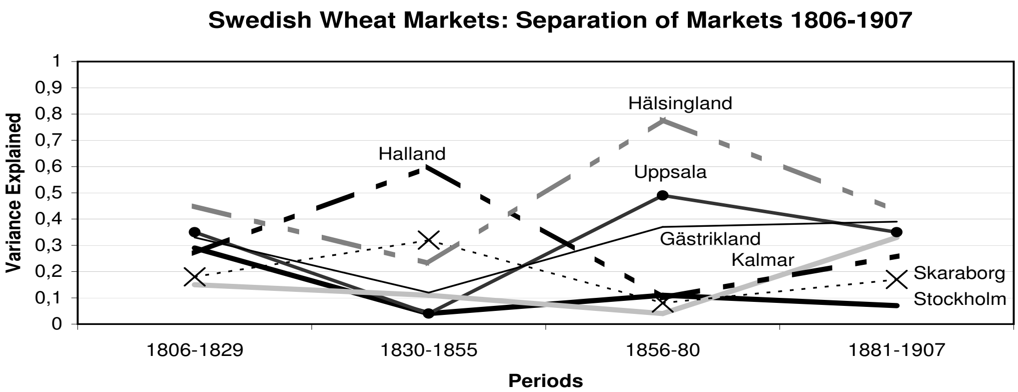
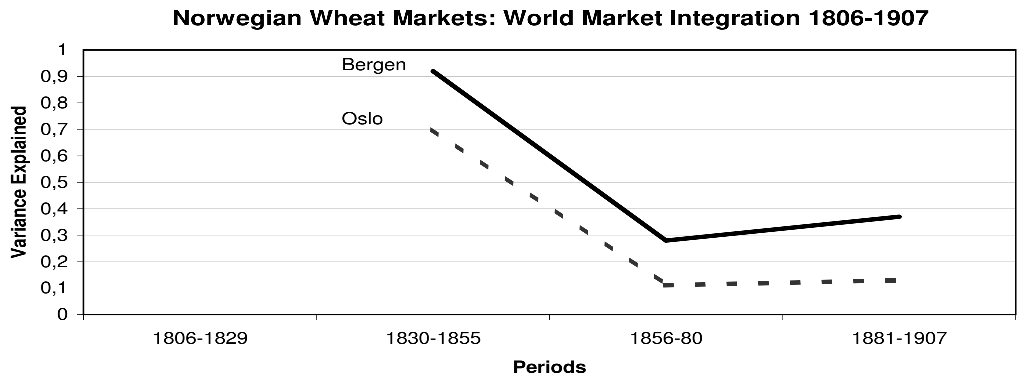
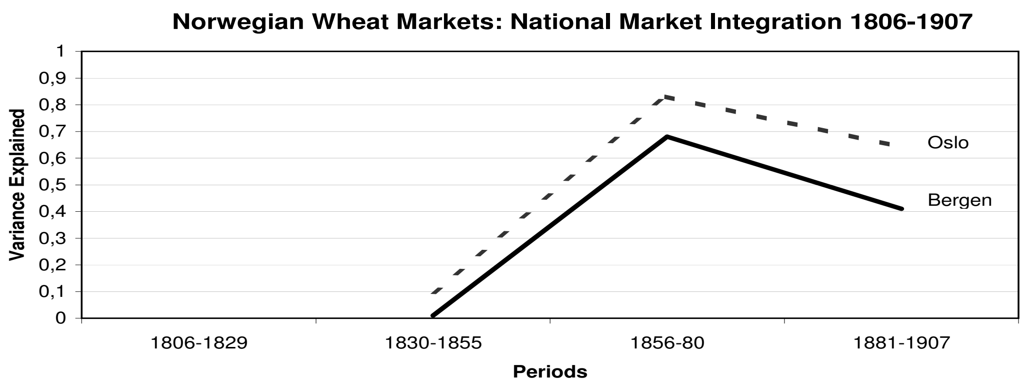
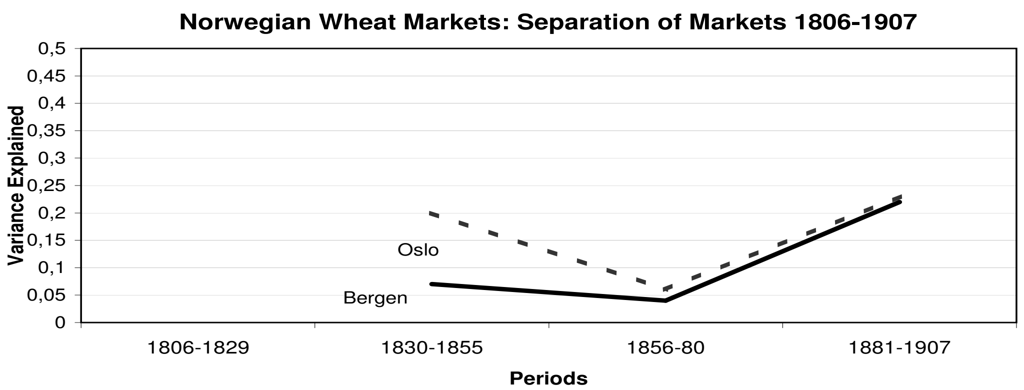


Figure 5.16: Development of world, national and local component in Norway, 1806-1907.







Chapter 6

Conclusion

This thesis contains four studies about Europe and the USA covering mainly the 19th century. It addresses cyclical historiography in a rapid growth environment, in particular Germany from the middle of the 19th century until World War I. In addition to the timing of particular cycles it also deals with when Germany's transition from an agricultural to an industrial economy occurred. The next research question is about cyclical activity in second moments, attempting to contribute to the discussion on the change of aggregate volatility in the USA from before World War I to after World War II. The last study covers a related, but different aspect of industrialization: the development of national and international markets for bulky commodities. Here, the focus is widened to the Atlantic economy. Due to the unique empirical setup, this study covers national wheat market integration in nine different nations, and yields evidence about how particular European and American cities integrated both nationally and internationally.

One chapter of this thesis applies spectral analysis as a method to compare time series on business cycle frequencies. The innovative character of this study arises from the use of financial data as an indicator of real activity. The method applied in three out of four chapters underlying this thesis is dynamic factor analysis. However, the particular empirical setups vary considerably. When analyzing the German business cycle timing, a single factor model with static factor loadings is chosen. The second moments of the business cycle, however, cannot be addressed with such a model. Thus, time varying coefficients are introduced that accommodate the effect of structural change as well as the time varying volatility of the factor. Market integration on two different levels is captured with a multi-factor model, which is the setup chosen in the last chapter.

Both studies about German business cycle timing in the 19th century yield the same pattern of booms and busts. They especially confirm the real upturn in the early 1870s, which was recently subject to debate.

The study on the U.S. finds that a moderation of cyclical swings after World

War II compared to the 19th century is unlikely. This outcome relies on the comparison of results of constant with a time-varying parameter model. The results suggest that there was no moderation of U.S. business cycle volatility between the 19th century and the postwar period, but that the perception of a moderation may be due to restricting the model to time invariant parameters. The result for the timing of German industrialization suggests an earlier transition than assumed so far. Finally, the multi-factor model applied to Atlantic wheat prices shows that international market integration improved more quickly in the first than in the second half of the 19th century. The dynamic pattern of prices paid in U.S. cities suggests that American markets only integrated into the world market after the Civil War.

One concern of this thesis – but by no means the sole one – is to highlight the contribution of the long term view to contemporary economics. Many economists' time horizon starts somewhere after World War II. However, understanding our current set of policy rules and economic conditions (both nationally and internationally) requires knowledge on how these rules have evolved. We cannot correctly assess the amplitude of recent economic swings if we are not aware of their 19th century counterparts when the international political and economic conditions were more comparable to today than to the interwar period. The results about the U.S. suggest that the impact of countercyclical economic policy after World War II may be overstated.

Evaluating trade liberalizations and the developments leading to them requires knowledge about the driving forces of market integration. We need to look at the past examples of trade liberalization and its interplay with technological advances in order to better understand current trade negotiations, and assess their likely impact. The evidence presented here cautions against simplistic explanations of international trade improvements such as steam technology after 1870, but emphasizes the impact of gradual technological advances combined with organizational enhancements.

Another concern is to show that economic history can benefit from current developments in applied econometrics. In fact, it could be even a mistake not to do so. Macro-econometrics has been developing rapidly in the recent past, and computational resources have become available to virtually everyone. Yet what has been accepted widely by empirical macro-economists is only slowly diffusing into the economic history literature. Applying recent econometrics to economic history therefore is likely to yield high marginal returns.

Economic historians confronted with scarce data therefore may find this thesis useful. The specific way to estimate the model, Bayesian statistics combined with Gibbs sampling, is flexible in accommodating data sets in many dimensions including large cross-sections and short time series. Without that feature, some of the projects in this thesis would have been impossible to conduct. The ability of the factor model to distinguish between idiosyncratic and common movements is found to be robust to the choice of the data set, although it remains a future task to assess this property quantitatively. Dynamic factor models can be successfully applied to annual time series, which is often the highest data frequency available.

It may be advisable to point out some caveats and suggest further possible research tasks. One is the undetermined volatility of the factor. Following the normalization of the data, the factor carries no information on scale. Therefore, this information must be attained from some other source. The scaling constants used here were obtained from national accounting. If national accounting aggregates are not available, however, a dynamic factor could be of little help when second moments are analyzed. Another riddle to be solved is the need to prepare the data and subtract a long term trend. Future formulations of dynamic factor models may include not only a common cycle but also a common trend, and, accordingly, series-specific cycles and trends.

One of the further research questions to be addressed could be the investigation of the historical business cycles of a larger group of countries. A comprehensive set of business cycle indicators derived from dynamic factor models could broaden the view on international economic processes and sharpen the understanding of national developments. This applies especially to countries whose historical national accounts cannot reach back before World War I.

Among others, the history of command economies is another fascinating subject to analyze with a dynamic factor model. The few historical national accounts for these nations lack the basic preconditions, because of the absence of market prices that are needed for aggregation. The same holds for countries subject to other kinds of market restrictions or episodes of strong price controls.

Once results for a certain number of countries are obtained, these data sets could be combined to large scale multi-factor models designed for modeling the international business cycle.

As is shown in the chapter on market integration, the analysis of price data is another promising avenue of further research. Index number problems in creating price indices can be circumvented by estimating a common factor from a wide array of commodity prices. This yields a measure of the prices that do not change relatively to each other but only in accord – exactly what a price level is supposed to reflect. Research projects could for example investigate the impact of silver inflows during the 17th century to mainland Europe. The discussion of the Great Divergence between Europe and Asia could be fueled by these price level estimates. Finally, the insights gained from the application to historical questions could help to solve problems of empirical research in contemporary environments where data is scarce. These could be developing countries that suffer from poor official statistics, large shadow economies or governments that are reluctant to disseminate information at the cost of the people. I would be happy if the insights from this thesis could inspire further research in this direction.

Appendix A

Appendix to Chapter 3

A.1 Data Sources Spree (1978)

A.1.1 1820-1850

- Sugar consumption in the years 1822-1849 was extrapolated with data from *Festschrift* of the German sugar industry [Deutsche Zucker-Industrie, 1925], and from Helling [1965] and the discount rate for 1820 and 1821.
- The crop production series by Hoffmann [1965] is supplemented by potato and wheat production for Prussia, Saxony, Bavaria and Württemberg [Helling, 1977].
- 1831-1834 yarn production comes from Dieterici [1931], 1820-30 is extrapolated using cotton imports and single data points from Kirchhain [1973].
- Scottish import prices 1830-1852 are supplemented with FOB-prices in Glasgow and 1820-1830 with prices for English iron in Hamburg.
- Iron production prior to 1834 is extrapolated using data from Prussia, Saxony and Nassau given in Marchand [1939]. Alsace-Lorraine is included after 1871, prior to that the *Zollverein* is covered.
- Private discount rates are reported from Bremen for 1820-1824, from Hamburg for 1824-1870 and from Berlin 1870-1913.

A.1.2 1851-1913

- The demographic series were originally assembled by Hoffmann [1965]. Also net crop production and sugar consumption are provided here.
- Prussian coal mining and labor productivity in Dortmund are provided by Holtfrerich [1973].

- Kirchhain [1973] delivers most of the textile industry series, i.e. spinning profits, yarn production, and gross cotton investment.
- All wholesale prices can be found in Jacobs and Richter [1935].
- Marchand [1939] is the main source for pig iron production.
- The interest rates and bills of exchange series are assembled from many different sources. The main sources are Müssig [1919] and Soetbeer [1886, 1855] for the private discount rate. Spree [1977] provides the core for the bills of exchange series supplemented by Spiethoff [1955].
- The bankruptcies series can be found in Gehrmann [1973].

A.2 Results Overview

Table A.1: Activity index coefficients (λ) and R^2s

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
		18, 1820-1850		18, 1820-1880		18, 1820-1913		6, 1820-1913	
	Series	λ	R^2	λ	R^2	λ	R^2	λ	R^2
1	Population	0.63	0.74	-0.01	0.01	0.07	0.00		
2	Births	0.00	0.00	0.02	0.00	-0.06	0.00		
3	Marriages	-0.11	0.02	0.15	0.04	0.05	0.04		
4	Death rate	-0.19	0.00	0.05	0.03	0.14	0.01		
5	Bankruptcies	-0.29	-0.01	-0.15	0.16	-0.1	0.08		
6	Bill discount rate Hamburg/Berlin	0.59	0.50	0.35	0.17	0.28	0.30	0.42	0.34
7	Stocks of bills of exchange	0.14	0.08	0.12	0.10	0.19	0.13	0.22	0.13
8	Food crop production					-0.05	0.00		
9	Wholesale prices food products	0.30	0.25	0.15	0.08	0.16	0.09		
10	Sugar consumption	0.11	0.00	-0.01	0.00	0.05	0.00		
11	Wholesale prices industrial raw materials	0.39	0.31	0.43	0.70	0.44	0.76	0.50	0.78
12	Prussian coal output	0.32	0.19	0.20	0.33	0.31	0.41	0.36	0.36
13	Labor productivity coal mining Dortmund	0.44	0.03	0.09	0.00	0.12	0.07		
14	Pig iron production	0.40	0.50	0.37	0.68	0.43	0.60	0.39	0.57
15	Price of Scottish pig iron in Hamburg	0.38	0.38	0.30	0.34	0.34	0.47	0.44	0.56
16	Gross investment cotton spinning	0.32	0.43	0.06	0.03	0.16	0.07		
17	Profits spinning industry	-0.03	0.00	-0.06	0.02	-0.09	0.01		
18	Yarn production	-0.19	0.00	-0.09	0.00	-0.04	0.00		
19	Wheat and potatoes Prussia	-0.32	0.10	0.02	0.00				
20	Wheat and potatoes Saxony	-0.29	0.20	-0.07	0.00				
21	Wheat and potatoes Bavaria	0.41	0.22	0.19	0.10				
22	Wheat and potatoes Württemberg	-0.25	0.08	0.02	0.03				

A.3 All Data Series

Table A.2: All series, subsets in colums.

Units: M = Mark, nr = number, pf = pfennig = 1/100 Mark, t = 1000k, zt. = 50kg, m = million, cap. = capita
Area: G = German Reich, P = Prussia, Z/G = Zollverein/German Reich
Subfactors: 18 = 18 series 1820-1913, 93 = 93 series 1840-1880, Ind. = 31 series heavy industries
Const. = 5 series construction, Tex. = 29 series textile industry, Agr. = 22 series agriculture

	Series	Units	Area	6	18	93	Ind.	Cnst.	Tex.	Agr.
1	population	1000	rnb		x	x				
2	price index of ind. raw materials	1913=1		x	x	x				
3	wholesale price index	1913=1				x				x
4	corporate bankruptcies	nr	rnb		x	x				
5	corporate bankruptcies in Prussia	nr				x				
6	corporate bankruptcies in Saxony	nr				x				
7	nr of workers Pruss. mining ind.	nr								
8	prod. Pruss. mining ind.	1000t								
9	value of prod. Pruss. mining ind.	1000M								
10	wage index German mining ind.	1900=1								
11	nr of workers mining ind.	nr	Z/G							
12	coal prod.	1000t	Z/G							
13	value of coal prod.	1000M	Z/G							
14	price index for coal	1913=1	Z/G							
15	price for English coal in Hamburg	M/t				x	x			
16	nr of workers coal mining ind.	nr								
17	coal prod. Pruss. mining ind.	mt		x	x	x	x			
18	value of coal prod. Pruss. mining ind.	1000M								
19	total ann. wages Pruss. coal mining ind.	mM								
20	total ann. wages Ruhr valley coal mining ind.	mM								
21	avg. ann. wages, Pruss. coal mining ind.	M/cap				x	x			
22	ann. wages Upper Silesia	M/cap				x	x			
23	ann. wages Ruhr valley					x	x			
24	ann. wages Saarland	M/cap				x	x			
25	avg. price of Pruss. coal ex mine	M/t				x	x			
26	avg. price of Lower Silesian coal ex mine	M/t				x	x			
27	avg. price of Upper Silesian coal ex mine	M/t				x	x			
28	avg. price of Ruhr valley coal ex mine	M/t				x	x			
29	avg. price of Saarland coal ex mine	M/t				x	x			
30	gross revenues, Ruhr valley coal mining ind.	mM								
31	indicator of capital income, Pruss. coal mining	1000M				x	x			
32	ratio capital/labor income Pruss. coal mining									
33	shared profits Ruhr valley coal prod.	M/t								
34	capital return per ton Pruss. coal mining	M/t								
35	nrs of workers Saxonian coal mining					x	x			

	Series	Units	Area	6	18	93	Ind.	Cnst.	Tex.	Agr.
36	coal prod. Saxony	1000t				x	x			
37	total ann. wages Saxonian coal mining ind.	mM								
38	avg. ann. wages Saxonian coal mining ind.	M/cap				x	x			
39	index of gross value added German transport ind.	1880=1								
40	index of transport volume inland navigation ind.	1840=1				x				
41	nr times distance of persons carried by railway	mkm	G							
42	nr of tons times distance of freight transported	mkm	G							
43	revenue from person carriage German railways	mM				x				
44	revenue from freight transport German railways	mM				x				
45	avg. capital return German railways	%								
46	nr times distance of persons carried by railway	mkm	P							
47	nr of tons times distance of freight transported	mkm	P							
48	revenue from person carriage Pruss. railways	mM				x				
49	revenue from freight transport Pruss. railways	mM				x				
50	index of construction activity	1913=1				x		x		
51	wage index German construction ind.	1900=1				x		x		
52	price index building materials constant weights	1913=1				x		x		
53	whs. price index building materials variable weights	1913=1								
54	whs. price index for lime	1913=1				x		x		
55	avg. price of lumber	M				x		x		
56	nr of workers metallurgical ind.	nr								
57	prod. volume Pruss. metallurgical ind.	1000t								
58	prod. value Pruss. metallurgical ind.	1000M								
59	nr of workers Pruss. iron ind.	nr				x	x			
60	prod. volume Pruss. iron ind.	1000t				x	x			
61	prod. value Pruss. iron ind.	1000M					x			
62	nr of workers pig iron ind.	nr	Z/G			x	x			
63	consumption of bar iron incl. rails	1000t	Z/G			x	x			
64	index of steel prod.	1913=1				x	x			
65	nr of workers non-iron metallurgical ind.	nr	Z/G			x	x			
66	prod. volume non-iron metallurgical ind.	1000t	Z/G			x	x			
67	prod. value non-iron metallurgical ind.	1000M	Z/G							
68	lead prod.	1000t	Z/G			x	x			
69	copper prod.	1000t	Z/G			x	x			
70	nr of worker non-iron metallurgical ind.	nr	P							
71	prod. volume non-iron metallurgical ind.	1000t	P							

	Series	Units	Area	6	18	93	Ind.	Cnst.	Tex.	Agr.
72	prod. value non-iron metallurgical ind.	1000M	P							
73	pig iron prod. volume	1000t	Z/G	x	x	x	x			
74	pig iron prod. value	1000M	Z/G							
75	avg. price metallurgical products ex works	M/t				x	x			
76	price index of iron	1870=1								
77	price index of non-iron metals constant weights	1913=1	Z/G							
78	price index of non-iron metals variable weights	1913=1	Z/G							
79	avg. price of copper ex works	M/kg				x	x			
80	price of zinc Upper Silesia ex works	M/zt.				x	x			
81	avg. price of pig iron ex works	M/t	Z/G			x	x			
82	price of Scottish pig iron ex Hamburg	M/t		x	x	x	x			
83	index of machine building	1880=1				x				
84	price index of ind. equipment and inventories	1913=1				x				
85	price index of agricultural machines	1913=1				x				
86	price index of steam engines	1913=1				x				
87	price index of investment goods	1913=1				x				
88	prod. index of textile ind.	1840=1							x	
89	price index of textiles constant weights	1913=1							x	
90	price index of textiles variable weights	1913=1								
91	exp. volume raw cotton	1000t	Z/G			x			x	x
92	imp. volume raw cotton	1000t	Z/G			x			x	x
93	price of cotton ex Bremen/Hamburg	M/kg				x			x	x
94	prod. of yarn	1000t			x	x			x	
95	stock of cotton spindles	units							x	
96	avg. ann. wages spinning ind.	M/cap				x			x	
97	exp. volume yarn	1000zt.	Z/G						x	
98	imp. volume yarn	1000zt.	Z/G						x	
99	avg. price of yarn	M/kg				x			x	
100	unit profits spinning ind.	M/kg			x	x			x	
101	prod. cotton weaving	1000t				x			x	
102	exp. volume cotton products	1000zt.				x			x	
103	imp. volume cotton products	1000zt.	Z/G			x			x	
104	unit profits weaving ind.	M/kg							x	
105	avg. price cotton textile	M/kg				x			x	
106	price index for linen	1913=1				x			x	
107	exp. volume wool	1000zt.				x			x	x
108	imp. volume wool	1000zt.	Z/G			x			x	x
109	price index for wool	1913=1				x			x	x
110	prod. index of woollen yarn	1913=1							x	
111	prod. index of woollen textiles	1913=1								
112	consumption of woollen textiles	1000t	Z/G			x			x	
113	exp. volume woollen textiles	1000zt.							x	
114	imp. volume woollen textiles	1000zt.	Z/G						x	
115	prod. index of silk	1913=1				x			x	
116	prod. silk products	1000t							x	
117	price index of raw silk	1913=1				x			x	
118	indicator of note circulation year end	mM								
119	total deposits retail banks year end	mM				x				
120	total deposits commercial banks year end	mM								

	Series	Units	Area	6	18	93	Ind.	Cnst.	Tex.	Agr.
121	lombard loans of retail and credit banks year end	mM				x				
122	total value of bills of exchange retail banks year end	mM		x	x	x				
123	avg. price of bonds German stock markets	%								
124	avg. effective return on Pruss. government bonds	%								
125	avg. bank discount rate Hamb./Berl.	%		x	x	x				
126	ann. high of bank discount rate Prussia	%								
127	ann. low of bank discount rate Prussia	%								
128	ann. high of private disc. rate Berlin stock market	%								
129	ann. low of private disc. rate Berlin stock market	%								
130	avg. private discount rate Hamburg stock market	%				x				
131	ann. high of discount rate Hamburg stock market	%								
132	ann. low of private disc. rate Hamburg stock market	%								
133	prod. index food, beverage and tobacco ind.	1913=1								x
134	avg. prices of imp.ed coffee ex Hamburg	M/1kg								
135	prod. volume sugar ind.	1000t								x
136	price of sugar in Berlin	M/1kg								
137	avg. price of sugar in Hamburg	M/1kg								
138	value of net agricultural prod. 1913 prices	mM			x	x				x
139	value of net agricultural prod. current prices	mM								
140	prod. price index agricultural products	1913=1			x	x				x
141	price index of rye in Berlin	1913=1				x				x
142	exp. price of rye in Hamburg	M/t				x				x
143	price index of wheat in Berlin	1913=1								x
144	exp. price of wheat in Hamburg	M/t								x
145	exp. of rye	1000t	Z/G			x				x
146	imp. of rye	1000t	Z/G			x				x
147	exp. of wheat	1000t	Z/G							x
148	imp. of wheat	1000t	Z/G							x
149	exp. value of Europ. foodstuffs const. prices	mM	Z/G			x				x
150	imp. value of Europ. foodstuffs const. prices	mM	Z/G							x
151	exp. value of raw materials const. prices	mM	Z/G			x				
152	exp. value of intermediate products const. prices	mM	Z/G							
153	exp. value finished products const. prices	mM	Z/G			x				
154	total exp. value const. prices	mM	Z/G			x				
155	imp. value Europ. foodstuffs const. prices	mM	Z/G			x				

	Series	Units	Area	6	18	93	Ind.	Cnst.	Tex.	Agr.
156	imp. value colonial foodstuffs const. prices	mM	Z/G							
157	imp. value of raw materials const. prices	mM	Z/G			x				
158	exp. value colonial foodstuffs const. prices	mM	Z/G							

A.4 Comparison of Activity Index With NNP-Estimates

Figure A.1: Activity index from 18 time series vs Burhop and Wolff's (2005) "Expenditure", "Income", and "Taxes"NNP-estimates.

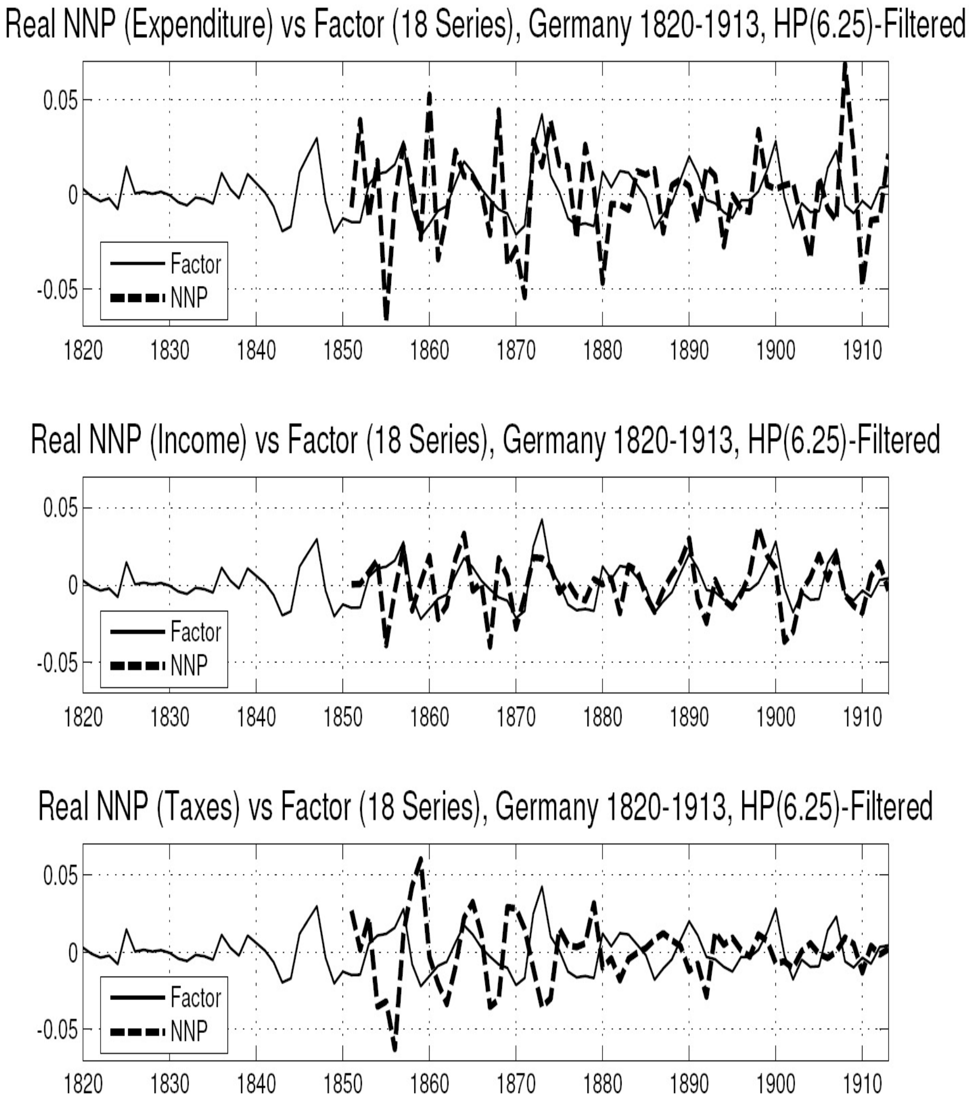
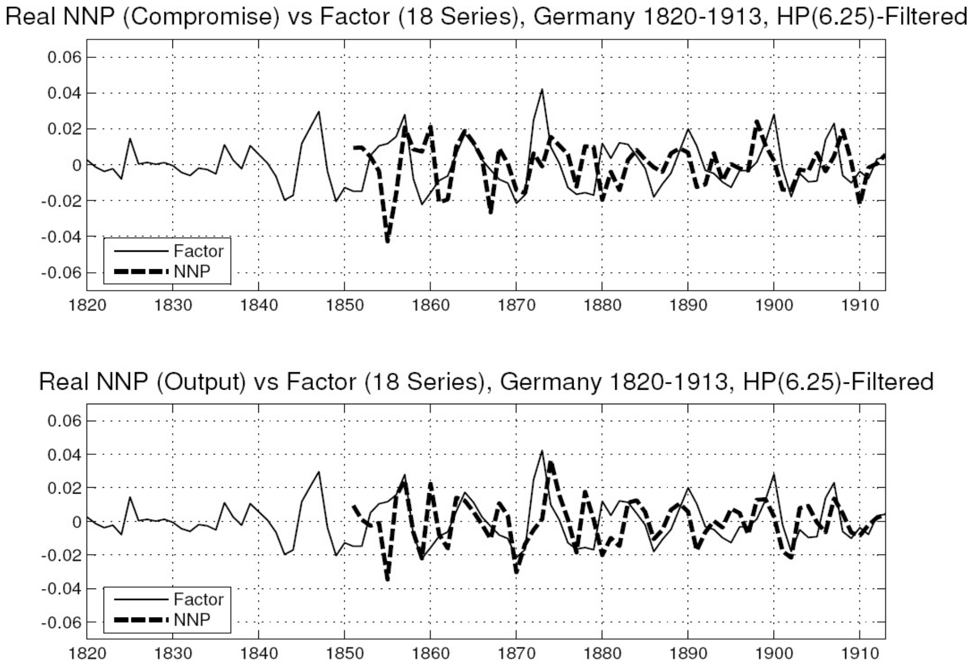


Figure A.2: Factor from 18 time series vs Burhop and Wolff's (2005) "Compromise", and "Output" NNP-estimates.



Appendix B

Appendix to Chapter 4

B.1 Estimating the Parameters

In this section we condition on the factor f_t and the factor loadings Λ_t.[1] Because equation (5.2) is a set of N independent regressions with autoregressive error terms it is possible to estimate $\Theta_1, \Theta_2, \ldots, \Theta_p$, Ω_χ and Ω_ε equation by equation. We rewrite equation (4.3) as:

$$u_i = X_{i,u}\theta_i + \chi_i \tag{B.1}$$

where $u_i = [u_{i,p+1}\ u_{i,p+2}\ \ldots\ u_{i,T}]'$ is $T-p \times 1$, $\theta_i = [\theta_{i,1}\ \theta_{i,2}\ \ldots\ \theta_{i,p}]'$, is $p \times 1$ and $\chi_i = [\chi_{i,p+1}\ \chi_{i,p+2}\ \ldots\ \chi_{i,T}]'$ is $T-p \times 1$ and

$$\left[X_{i,u}\right] = \begin{bmatrix} u_{i,p} & u_{i,p-1} & \cdots & u_{i,1} \\ u_{i,p+1} & u_{i,p} & \cdots & u_{i,2} \\ \vdots & \vdots & \vdots & \vdots \\ u_{i,T-1} & u_{i,T-2} & \cdots & u_{i,T-p} \end{bmatrix}$$

which is a $T-p \times p$ for $i = 1, 2, \ldots, N$.

Combining the priors described in section 4.3.2 with the likelihood function we obtain the following posterior distributions.

The posterior of the AR-parameters of the idiosyncratic components is:

$$\theta_i \sim N(\overline{\theta_i}, \overline{V}_{i,\theta}) I_{S_\theta} \tag{B.2}$$

where

$$\overline{\theta_i} = \left(\underline{V_\theta}^{-1} + (\sigma^2_{i,\chi})^{-1} X'_{i,u} X_{i,u}\right)^{-1} \left(\underline{V}_\theta^{-1}\underline{\theta} + (\sigma^2_{i,\chi})^{-1} X'_{i,u} u_i\right)$$

and

$$\overline{V}_{i,\theta} = \left(\underline{V}_\theta^{-1} + (\sigma^2_{i,\chi})^{-1} X'_{i,u} X_{i,u}\right)^{-1}.$$

where I_{S_θ} is an indicator function enforcing stationarity.

[1] The technical part of this appendix was written by Samad Sarferaz.

The posterior of the variance of the idiosyncratic component $\sigma_{i,\chi}$ is:

$$\sigma_{i,\chi} \sim \mathscr{IG}\left(\frac{(T+\alpha_\chi)}{2}, \frac{((u_i - X_i\theta_i)'(u_i - X_i\theta_i) + \delta_\chi)}{2}\right) \tag{B.3}$$

The posterior of the variance of the factor loadings $\sigma_{i,\varepsilon}$ is:

$$\sigma_{i,\varepsilon} \sim \mathscr{IG}\left(\frac{(T+\alpha_\varepsilon)}{2}, \frac{((\Delta\lambda_i)'(\Delta\lambda_i) + \delta_\varepsilon)}{2}\right) \tag{B.4}$$

To estimate the AR-parameters of the factor $\varphi_1, \varphi_2, \ldots, \varphi_q$ we find it useful to rewrite equation (5.4) as:

$$f = X_f\varphi + \nu \tag{B.5}$$

where $f = [f_{q+1}\ f_{q+2}\ \ldots\ f_T]'$ is $T-q \times 1$, $\varphi = [\varphi_1\ \varphi_2\ \ldots\ \varphi_q]'$ is $q \times 1$, $\nu = [\nu_{q+1}\ \nu_{q+2}\ \ldots\ \nu_T]'$ is $T-q \times 1$ and

$$[X_f] = \begin{bmatrix} f_q & f_{q-1} & \cdots & f_1 \\ f_{q+1} & f_q & \cdots & f_2 \\ \vdots & \vdots & \vdots & \vdots \\ f_{T-1} & f_{T-2} & \cdots & f_{T-q} \end{bmatrix}$$

which is $T-q \times q$. Thus, the posterior of the AR-parameters of the factor is:

$$\varphi \sim N(\overline{\varphi}, \overline{V}_\varphi) I_{S_\varphi} \tag{B.6}$$

where

$$\overline{\varphi} = \left(\underline{V_\varphi}^{-1} + (X_f'X_f)\right)^{-1}\left(\underline{V}_\varphi^{-1}\underline{\varphi} + (X_f'f)\right)$$

and

$$\overline{V}_f = \left(\underline{V}_\varphi^{-1} + X_f'X_f\right)^{-1}$$

where I_{S_φ} is an indicator function enforcing stationarity.

To estimate the factor loadings, when they are assumed to be constant, we rewrite equation (5.2) as:

$$y_i^* = \lambda_i f^* + \chi \tag{B.7}$$

where $y_i^* = [(1-\theta(L)_i)y_{i,p+1}\ (1-\theta(L)_i)y_{i,p+2}\ \ldots\ (1-\theta(L)_i)y_{i,T}]'$ which is $T-p \times 1$ and $f^* = [(1-\theta(L)_i)f_{p+1}\ (1-\theta(L)_i)f_{p+2}\ \ldots\ (1-\theta(L)_i)f_T]'$, which is $T-p \times 1$ with $\theta(L)_i = (\theta_{i,1} + \theta_{i,2} + \cdots + \theta_{i,p})$ for $i = 1, 2, \ldots, N$. Thus, the posterior for the constant factor loadings is:

$$\lambda_i \sim N(\overline{\lambda_i}, \overline{V}_{i,\lambda}) \tag{B.8}$$

where

$$\overline{\lambda_i} = \left(\underline{V_\lambda}^{-1} + (\sigma_{i,\chi}^2)^{-1} f^{*\prime} f^*\right)^{-1} \left(\underline{V}_\lambda^{-1} \underline{\lambda} + (\sigma_{i,\chi}^2)^{-1} f^{*\prime} y_i^*\right)$$

and

$$\overline{V}_{i,\lambda} = \left(\underline{V}_\lambda^{-1} + (\sigma_{i,\chi}^2)^{-1} f^{*\prime} f^*\right)^{-1}.$$

B.2 Estimating the Latent Factor

To estimate the common latent factor we condition on the parameters of the model $\Xi \equiv (\varphi_1, \varphi_2, \ldots, \varphi_q, \Theta_1, \Theta_2, \ldots, \Theta_p)$ and the factor loadings Λ_t. We begin by quasi-differencing equation (5.2) and use it as our observation equation in the following state-space system:

$$Y_t^* = H_t F_t + \chi_t \tag{B.9}$$

where

$$Y_t^* = (\mathscr{I}_N - \Theta(L))Y_t$$
$$H_t = [\Lambda_t \ -\Theta_1\Lambda_{t-1} \ -\Theta_2\Lambda_{t-2} \ \ldots \ \Theta_p\Lambda_{t-p} \ 0_{N\times q-p-1}]$$

with

$$\Theta(L) = (\Theta_1 + \Theta_2 + \cdots + \Theta_p)$$

Our state equation is:

$$F_t = \Phi F_{t-1} + \widetilde{v}_t \tag{B.10}$$

where $F_t = [f_t, f_{t-1}, \ldots, f_{t-q+1}]'$ is $q \times 1$, which is denoted as the state vector, $\widetilde{v}_t = [v_t \ 0 \ \ldots \ 0]'$ is $q \times 1$ and

$$[\Phi] = \begin{bmatrix} \varphi_1 & \varphi_2 & \cdots & \varphi_q \\ & \mathscr{I}_{q-1} & & 0_{q-1\times 1} \end{bmatrix}$$

which is $q \times q$. For all empirical results shown below we use $q > p$.

To calculate the common factor we use the algorithm suggested by Carter and Kohn [1994] and Frühwirth-Schnatter [1994]. This procedure draws the vector $F = [F_1 \ F_2 \ \ldots \ F_T]$ from its joint distribution given by:

$$p(F|\Lambda, Y, \Xi) = p(F_T|\Lambda_T, y_T, \Xi) \prod_{t=1}^{T-1} p(F_t|F_{t+1}, \Lambda_t, \Xi, Y^t) \tag{B.11}$$

where $\Lambda = [\Lambda_1 \ \Lambda_2 \ \ldots \ \Lambda_T]$ and $Y^t = [Y_1 \ Y_2 \ \ldots \ Y_t]$. Because the error terms in equations (B.9) and (B.10) are Gaussian, equation (B.11) can be rewritten as:

$$p(F|\Lambda, Y, \Xi) = N(F_{T|T}, P_{T|T}) \prod_{t=1}^{T-1} N(F_{t|t,F_{t+1}}, P_{t|t,F_{t+1}}) \tag{B.12}$$

with

$$F_{T|T} = \quad E(F_T|\Lambda,\Xi,Y) \tag{B.13}$$
$$P_{T|T} = \quad Cov(F_T|\Lambda,\Xi,Y) \tag{B.14}$$

and

$$F_{t|t,F_{t+1}} = \quad E(F_t|F_{t+1},\Lambda,\Xi,Y) \tag{B.15}$$
$$P_{t|t,F_{t+1}} = \quad Cov(F_t|F_{t+1},\Lambda,\Xi,Y) \tag{B.16}$$

We obtain $F_{T|T}$ and $P_{T|T}$ from the last step of the Kalman filter iteration and use them as the conditional mean and covariance matrix for the multivariate normal distribution $N(F_{T|T},P_{T|T})$ to draw F_T. To illustrate the Kalman Filter we work with the state-space system equations (B.9) and (B.10). We begin with the prediction steps:

$$F_{t|t-1} = \quad \Phi F_{t-1|t-1} \tag{B.17}$$
$$P_{t|t-1} = \quad \Phi P_{t-1|t-1}\Phi + Q \tag{B.18}$$

where

$$[Q] = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}$$

which is $q \times q$. To update these predictions we first have to derive the forecast error:

$$\kappa_t = Y_t^* - H_t F_{t|t-1} \tag{B.19}$$

its variance:

$$\Sigma = H_t P_{t|t-1} H_t' + \Omega_\chi \tag{B.20}$$

and the Kalman gain:

$$K_t = P_{t|t-1} H_t' \Sigma^{-1}. \tag{B.21}$$

Thus, the updating equations are:

$$F_{t|t} = \quad F_{t|t-1} + K_t \kappa_t, \tag{B.22}$$
$$P_{t|t} = \quad P_{t|t-1} + K_t H_t P_{t|t-1}, \tag{B.23}$$

To obtain draws for $F_1, F_2, \dots, F_{T-1}$ we sample from $N(F_{t|t,F_{t+1}}, P_{t|t,F_{t+1}})$, using a backwards moving updating scheme, incorporating at time t information about F_t contained in period $t+1$. More precisely, we move backwards and generate F_t for $t = T-1, \dots, p+1$ at each step while using information from the Kalman filter and F_{t+1} from the previous step. We do this until $p+1$ and calculate $f_1, f_2, \dots, f_p$ in an one-step procedure.

The updating equations are:

$$F_{t|t,F_{t+1}} = F_{t|t} + P_{t|t}\Phi' P^{-1}_{t+1|t}(F_{t+1} - F_{t+1|t}) \tag{B.24}$$

and

$$P_{t|t,F_{t+1}} = P_{t|t} - P_{t|t}\Phi' P^{-1}_{t+1|t}\Phi P_{t|t} \tag{B.25}$$

B.3 Estimating the Time-Varying Factor Loadings

To estimate the time-varying factor loadings we condition on the parameters Ξ and the factor f_t. Because equation (5.2) and equation (4.4) are N independent linear regressions, the factor loadings can be estimated equation by equation. Hence, we use the following state-space system and begin with the observation equation:

$$y^*_{i,t} = z_{i,t}\widetilde{\lambda}_{i,t} + \chi_{i,t} \tag{B.26}$$

where $y^*_{i,t} = (1-\theta(L)_i)y_{i,t}$, $z_{i,t} = [f_t \ -\theta_{i,1}f_{t-1} \ \dots \theta_{i,p}f_{t-p}]$, which is $1 \times p+1$, $\widetilde{\lambda}_{i,t} = [\lambda_{i,t} \ \lambda_{i,t-1} \ \dots \ \lambda_{i,t-p}]'$, which is $p+1 \times 1$ and with $\theta(L)_i = (\theta_{i,1} + \theta_{i,2} + \dots + \theta_{i,p})$ for $i = 1, 2, \dots, N$.

The state equation is:

$$\widetilde{\lambda}_{i,t} = A\widetilde{\lambda}_{i,t-1} \tag{B.27}$$

where

$$[A] = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ & \mathscr{I}_p & & 0_{p\times 1} \end{bmatrix}$$

which is $p+1 \times p+1$. After we have defined the state-space system, calculating the time-varying factor loadings is straightforward as we just have to apply the Carter and Kohn [1994] and Frühwirth-Schnatter [1994] algorithm described above.

Because $\widetilde{\lambda}_{i,t}$ follows a driftless random walk and hence is not a stationary process it is not possible to use the unconditional mean and variance as starting values for the Kalman filter anymore [Hamilton, 1994, 378]. Thus, we decided to use the estimates for the constant factor loadings as a proxy for the initial conditions.[2]

[2] We applied this to simulated data and obtained very satisfying results.

B.4 Data Sources

Table B.1: Data Series, Units, and Sources.

	Series	Code	Units
1	Cargo moved on NY State canals	Df696	Short tons
2	Wholesale price cotton, raw	m04006a	Cents per pound
3	Oats production	Da667-678	Thousand metric tons
4	Cotton production	Da755-765	Thousand short tons
5	Patents granted	Cg38	Patents granted
6	Stock prices	Cj797	Stock prices
7	US Notes	Cj60	US Notes
8	Business failures	Ch411	Total
9	Coal fuel mineral production	Db25-33	Thousand short tons
10	Vessels entered US ports	Df594	Total
11	Wool prices	Cc205-266	Dollars
12	Coal prices	Cc237	Dollars
13	Irish potatoes acreage	Da768	Thousand acres
14	Irish potatoes production	Da769	Thousand tons
15	Irish potatoes price	Da770	Dollars per hundredweight
16	Cattle number	Da968	Total
17	Cattle price	Da969	Value per head
18	Hogs number	Da970	Total
19	Hogs price	Da971	Value per head
20	Cows and heifers	Da1020	Total
21	Cows and heifers	Da1021	Value per head
22	Petroleum price	Db56	Average value at well
23	Bit. Coal Imports	Db60	Thousand short tons
24	Pig iron shipments	Db74	Thousand metric ton
25	Production from mines	Db75	Metric tons
26	Lead production	Db80	Metric tons
27	Zinc production	Db84	Metric tons
28	Gold production	Db94	Kilograms
29	Silver production	Db 95	Metric tons
30	Refined lead imports	Db46	Thousand metric tons
31	Coal exports	Db191	Thousand short tons
32	Wheat flour[3]	Dd368	Thousand short tons
33	Hot rolled iron and steel	Dd405	Thousand short tons
34	Rails	Dd407	Thousand short tons
35	Corn harvested for grain	Da697	Acreage harvested
36	Coffee, imported	Dd843	Million pounds
37	Barley acreage	Da701	Thousand acres
38	Barley	Da702	Thousand bushels
39	Flaxseed	Da705	Dollars per hundredweight
40	Exports of merchandise, gold, and silver	Ee362	Dollars
41	Imports of merchandise, gold, and silver	Ee363	Dollars
42	Exports and imports	Ee1	Million dollars
43	Merchandise imports and duties	Ee 425	Dollars
44	All wheat acreage	Da717	Thousand acres
45	All wheat production	Da718	Million bushels
46	All wheat price	Da719	Million dollars
47	Hay acreage	Da733	Thousand acres
48	Hay production	Da734	Thousand tons

[3] Two data points have been exchanged by interpolated values of their nearest neighbors, because they represented extreme outliers and are possibly due to errors in the data gathering procedure as we could not find qualitative evidence for a decrease in milling in the presence of continuing wheat production (1872/1893). Three missing values in the 1930s have been replaced by means.

	Series	Code	Units
49	Hay price	Da735	Million Dollars
50	Rye acreage	Da740	Thousand acres
51	Rye production	Da741	Thousand bushels
52	Rye price	Da742	Thousand acres
53	Population	Aa7	Total

Series from Carter et al. [2006] with *A* for vol. 1 to *D* for vol. 5. More details there and at `www.NBER.org`.

B.5 Robustness Checks

The table below shows the results from stationarizing the data for different filters. Figures shown are the medians and standard deviations of the respective dynamic factor obtained under various filters applied to the data. All results are shown for five different combinations of the tightness parameters on the factor loadings prior. The first column is from Hodrick-Prescott (6.25) filtered series, which is the specification used in the main body of the paper. The second column contains results from the Christiano and Fitzgerald [2003] filter with a pass band of 2-8 years, allowing cycles within that band to be included in the cyclical part of the series. The third column presents evidence from first differenced data, and the last column contains Baxter and King [1999] band pass filtered series, setting the window length of $K = 6$.

Table B.2: Robustness of alternative detrending methods.

FL Prior δ_ε / α_ε		HP 6.25	CF 2-8y.	DF	BK 2-8y.
ALL SERIES					
0.01 / 1	median	**2.36**	**1.49**	**1.80**	**2.61**
	std.dev.	0.30	0.18	0.22	0.34
0.1 / 10	median	**1.69**	**1.20**	**1.31**	**1.53**
	std.dev.	0.19	0.13	0.16	0.36
1 / 100	median	**1.32**	**1.14**	**1.23**	**1.10**
	std.dev.	0.15	0.12	0.16	0.13
0.01 / 1000	median	**1.02**	**0.83**	**1.04**	**0.79**
	std.dev.	0.07	0.05	0.08	0.05
Constant FL	median	**1.01**	**0.86**	**1.05**	**1.14**
	std.dev.	0.07	0.05	0.07	0.07
REAL SERIES					
0.01 / 1	median	**2.07**	**2.35**	**2.11**	**1.93**
	std.dev.	0.26	0.27	0.27	0.29
0.1 / 10	median	**1.87**	**2.02**	**1.37**	**1.86**
	std.dev.	0.23	0.24	0.20	0.22
1 / 100	median	**1.66**	**1.72**	**1.25**	**1.25**
	std.dev.	0.20	0.20	0.17	0.17
0.01 / 1000	median	**1.17**	**1.20**	**1.16**	**1.19**
	std.dev.	0.02	0.02	0.02	0.02
Constant	median	**1.18**	**0.88**	**0.92**	**0.99**
	std.dev.	0.03	0.06	0.06	0.07
NOMINAL SERIES					
0.01 / 1	median	**0.84**	**0.81**	**1.04**	**0.83**
	std.dev.	0.12	0.11	0.15	0.12
0.1 / 10	median	**0.85**	**0.75**	**1.01**	**0.86**
	std.dev.	0.12	0.11	0.15	0.13
1 / 100	median	**0.84**	**0.71**	**1.04**	**1.04**
	std.dev.	0.13	0.10	0.17	0.17
0.01 / 1000	median	**1.29**	**1.19**	**1.30**	**1.36**

FL Prior δ_ε / α_ε		HP 6.25	CF 2-8y.	DF	BK 2-8y.
	std.dev.	0.10	0.08	0.12	0.11
Constant	median	**1.22**	**1.16**	**1.15**	**1.21**
	std.dev.	0.09	0.09	0.09	0.09
NON-AGRICULTURAL SERIES					
0.01 / 1	median	**1.59**	**0.83**	**1.19**	**1.34**
	std.dev.	0.18	0.10	0.21	0.23
0.1 / 10	median	**1.42**	**0.82**	**1.17**	**1.33**
	std.dev.	0.16	0.11	0.16	0.17
1 / 100	median	**1.34**	**0.86**	**1.13**	**1.13**
	std.dev.	0.15	0.13	0.15	0.15
0.01 / 1000	median	**0.92**	**0.82**	**0.95**	**0.94**
	std.dev.	0.06	0.04	0.07	0.06
Constant	median	**0.94**	**0.84**	**0.99**	**1.03**
	std.dev.	0.06	0.05	0.07	0.06
AGRICULTURAL SERIES					
0.01 / 1	median	**1.28**	**1.01**	**0.91**	**1.26**
	std.dev.	0.18	0.12	0.12	0.16
0.1 / 10	median	**0.99**	**1.00**	**1.05**	**1.16**
	std.dev.	0.13	0.12	0.15	0.13
1 / 100	median	**1.21**	**1.00**	**0.99**	**0.99**
	std.dev.	0.16	0.11	0.12	0.11
0.01 / 1000	median	**1.23**	**1.29**	**1.13**	**1.17**
	std.dev.	0.09	0.09	0.08	0.07
Constant FL	median	**1.20**	**1.25**	**1.06**	**1.16**
	std.dev.	0.08	0.08	0.08	0.08
NON-AGRIGULTURAL REAL SERIES					
0.01 / 1	median	**1.77**	**2.34**	**2.02**	**1.90**
	std.dev.	0.24	0.28	0.26	0.25
0.1 / 10	median	**1.60**	**2.23**	**1.36**	**1.85**
	std.dev.	0.21	0.31	0.21	0.23
1 / 100	median	**1.52**	**2.02**	**1.25**	**1.83**
	std.dev.	0.18	0.25	0.17	0.23
0.01 / 1000	median	**0.90**	**1.23**	**1.16**	**1.24**
	std.dev.	0.07	0.02	0.02	0.02
Constant FL	median	**0.85**	**0.92**	**0.94**	**1.24**
	std.dev.	0.05	0.06	0.06	0.08
NON-AGRICULTURAL NOMINAL SERIES					
0.01 / 1	median	**0.72**	**0.91**	**0.72**	**0.77**
	std.dev.	0.11	0.13	0.13	0.12
0.1 / 10	median	**0.83**	**0.95**	**0.95**	**0.78**
	std.dev.	0.13	0.13	0.15	0.11
1 / 100	median	**0.88**	**0.97**	**0.92**	**0.96**
	std.dev.	0.12	0.12	0.14	0.13
0.01 / 1000	median	**1.32**	**1.40**	**1.34**	**1.93**
	std.dev.	0.02	0.02	0.02	0.03
Constant FL	median	**0.83**	**0.99**	**0.87**	**0.87**

FL Prior δ_ε / α_ε		HP 6.25	CF 2-8y.	DF	BK 2-8y.
	std.dev.	0.10	0.15	0.13	0.08
AGRICULTURAL REAL SERIES					
0.01 / 1	median	**0.78**	**0.72**	**0.69**	**0.77**
	std.dev.	0.12	0.10	0.11	0.09
0.1 / 10	median	**0.65**	**0.69**	**0.66**	**0.69**
	std.dev.	0.09	0.10	0.08	0.07
1 / 100	median	**0.74**	**0.67**	**0.79**	**0.68**
	std.dev.	0.11	0.09	0.12	0.13
0.01 / 1000	median	**2.33**	**2.22**	**2.37**	**2.29**
	std.dev.	0.03	0.04	0.03	0.04
Constant FL	median	**2.14**	**2.19**	**2.23**	**2.07**
	std.dev.	0.17	0.15	0.20	0.18
AGRICULTURAL NOMINAL SERIES					
0.01 / 1	median	**0.91**	**0.72**	**0.99**	**1.13**
	std.dev.	0.12	0.10	0.14	0.17
0.1 / 10	median	**1.05**	**0.69**	**0.95**	**1.14**
	std.dev.	0.15	0.10	0.14	0.17
1 / 100	median	**0.99**	**0.67**	**1.08**	**1.20**
	std.dev.	0.12	0.09	0.16	0.18
0.01 /1000	median	**1.13**	**2.22**	**1.16**	**1.28**
	std.dev.	0.08	0.04	0.09	0.10
Constant FL	median	**1.16**	**1.16**	**1.09**	**1.23**
	std.dev.	0.08	0.08	0.08	0.09
NON-AGRICULTURAL REAL PRODUCTION SERIES					
0.01 / 1	median	**1.74**	**1.41**	**1.2**	**1.49**
	std.dev.	0.24	0.18	0.16	0.21
0.1 / 10	median	**1.60**	**0.96**	**1.21**	**1.14**
	std.dev.	0.21	0.05	0.17	0.15
1 / 100	median	**1.50**	**1.38**	**1.18**	**1.46**
	std.dev.	0.18	0.19	0.16	0.2
0.01 / 1000	median	**0.90**	**0.97**	**0.92**	**0.95**
	std.dev.	0.07	0.05	0.07	0.07
Constant FL	median	**0.83**	**0.93**	**1.14**	**0.94**
	std.dev.	0.05	0.05	0.04	0.06
NON-AGRICULTURAL REAL NON-PRODUCTION SERIES					
0.01 / 1	median	**1.33**	**1.53**	**1.69**	**1.61**
	std.dev.	0.20	0.22	0.23	0.23
0.1 / 10	median	**1.37**	**1.52**	**1.45**	**1.39**
	std.dev.	0.19	0.21	0.19	0.19
1 / 100	median	**1.09**	**1.63**	**1.50**	**1.42**
	std.dev.	0.16	0.22	0.24	0.19
0.01 / 1000	median	**1.38**	**1.56**	**1.40**	**1.40**
	std.dev.	0.03	0.18	0.02	0.02
Constant FL	median	**1.38**	**1.56**	**1.40**	**1.71**
	std.dev.	0.03	0.18	0.02	0.15

FL Prior	HP	CF	DF	BK
δ_ε / α_ε	6.25	2-8y.		2-8y.

HP = Hodrick-Prescott, CF = Christiano-Fitzgerald, DF = Difference Filter, BK = Baxter-King

Table B.3: Volatility by decade. 53 Series, 1867-1995, subsets, factor loadings with different degrees of time variation.

Dev. from HP-trend %	1867 -1913	1914 -29	1930 -39	1946 -95	1950 -59	1960 -69	1970 -79	1980 -95	Postwar /Prewar
Romer GNP	2.07	2.78	6.00	2.01	2.98	0.98	2.06	1.34	0.97
Balke/Gordon GNP	2.47	4.10	6.00	2.01	2.98	0.98	2.06	1.34	0.81
ALL 53 SERIES									
0.01-1	0.85	3.54	8.14	2.01	2.03	0.47	1.51	1.26	2.36
0.1-10	1.19	2.95	5.53	2.01	2.27	0.63	1.71	1.43	1.69
1-100	1.51	3.54	5.02	2.01	2.22	0.90	2.25	1.90	1.33
0.01-1000	1.97	5.20	6.92	2.01	2.47	1.11	1.84	1.75	1.02
Constant	2.00	5.25	6.92	2.01	2.49	1.12	1.86	1.74	1.01
NOMINAL SERIES									
0.01-1	2.40	4.56	6.98	2.01	1.36	0.81	3.03	1.68	0.84
0.1-10	2.39	4.34	7.03	2.01	1.42	0.86	2.97	1.67	0.85
1-100	2.40	4.07	5.45	2.01	1.43	0.92	3.03	1.73	0.84
0.01-1000	1.56	3.73	4.73	2.01	1.18	0.89	3.19	1.96	1.29
Constant	1.64	3.64	4.76	2.01	1.21	0.87	3.14	1.95	1.22
REAL SERIES									
0.01-1	0.97	2.23	3.61	2.01	1.69	1.23	1.15	1.65	2.07
0.1-10	1.07	2.14	3.62	2.01	1.90	1.32	1.40	1.75	1.87
1-100	1.21	2.27	3.82	2.01	2.19	1.46	1.64	1.58	1.66
0.01-1000	1.72	3.59	3.90	2.01	2.81	0.87	1.45	1.24	1.17
Constant	1.70	3.55	3.98	2.01	2.82	0.88	1.44	1.26	1.18
AGRICULTURAL SERIES									
0.01-1	1.57	4.26	7.04	2.01	2.32	0.90	2.58	1.47	1.28
0.1-10	2.04	3.62	6.32	2.01	2.26	0.94	2.67	1.88	0.99
1-100	1.67	3.03	5.82	2.01	2.14	0.90	2.60	1.87	1.21
0.01-1000	1.63	2.95	4.68	2.01	1.25	0.81	3.04	2.02	1.23
Constant	1.67	2.67	4.67	2.01	1.35	0.82	2.98	2.01	1.20
NON-AGRICULTURAL SERIES									
0.01-1	1.26	2.61	5.39	2.01	3.01	0.90	1.71	1.28	1.59
0.1-10	1.42	2.60	5.47	2.01	2.98	0.87	1.83	1.26	1.42
1-100	1.50	2.65	5.51	2.01	3.04	0.89	1.78	1.11	1.34
0.01-1000	2.19	5.27	5.74	2.01	2.85	1.11	2.00	1.29	0.92
Constant	2.15	5.05	6.88	2.01	2.73	1.11	1.50	1.66	0.94
NON-AGRICULTURAL NOMINAL SERIES									
0.01-1	2.80	5.05	5.34	2.01	1.74	1.41	2.76	1.39	0.72
0.1-10	2.41	3.43	4.30	2.01	1.73	1.46	2.74	1.56	0.83
1-100	2.29	2.49	3.23	2.01	1.63	1.44	2.87	1.61	0.88
0.01-1000	1.53	3.43	3.42	2.01	2.29	1.45	1.62	1.47	1.32
Constant	3.16	5.15	6.13	2.01	2.84	1.33	2.42	1.53	0.64
NON-AGRICULTURAL REAL SERIES									
0.01-1	1.14	2.09	3.62	2.01	1.91	1.19	1.25	1.64	1.77

Dev. from HP-trend %	1867 -1913	1914 -29	1930 -39	1946 -95	1950 -59	1960 -69	1970 -79	1980 -95	Postwar /Prewar
0.1-10	1.26	2.18	3.80	2.01	2.16	1.19	1.33	1.71	1.60
1-100	1.33	2.21	3.80	2.01	2.37	1.18	1.37	1.67	1.52
0.01-1000	2.22	4.86	6.63	2.01	2.71	1.12	1.64	1.73	0.90
Constant	2.36	5.03	6.64	2.01	2.69	1.06	1.79	1.79	0.85
AGRICULTURAL NOMINAL SERIES									
0.01-1	1.94	3.30	5.13	2.01	1.18	0.82	3.05	1.83	1.04
0.1-10	1.96	3.31	5.24	2.01	1.22	0.88	3.03	1.79	1.02
1-100	1.82	3.05	3.89	2.01	1.16	0.96	3.12	1.86	1.12
0.01-1000	1.63	3.29	4.43	2.01	1.05	0.86	3.14	1.99	1.24
Constant	1.74	3.04	4.47	2.01	1.09	0.88	3.10	1.93	1.16
AGRICULTURAL REAL SERIES									
0.01-1	2.56	2.76	4.08	2.01	2.06	1.35	2.07	2.30	0.78
0.1-10	3.12	3.30	4.73	2.01	2.32	1.63	2.31	1.60	0.65
1-100	2.74	3.06	4.72	2.01	2.33	1.71	2.37	1.59	0.74
0.01-1000	0.86	2.19	4.60	2.01	2.08	1.85	2.60	1.70	2.33
Constant	0.94	2.14	4.74	2.01	2.18	1.80	2.56	1.66	2.14

Factor estimated for 1867-1995 and standardized such that the standard deviation of the subperiod 1946-1995 matches Nipa's (1946-1995, 2000 prices) ($\sigma = 2.01$).

Appendix C

Appendix to Chapter 5

C.1 MCMC Draws

When using Gibbs sampling the non-standard distribution of the joint posterior of the factor and the parameters is divided into standard distributions that take the values of the other blocks as given. In the case of constant weights there are two blocks of conditional standard distributions:

- the parameters of the model conditioning on the factor $p(\Omega|f)$,
- the factor conditioning on the parameters $p(f|\Omega)$.

In particular, the parameters of the model used here are $\Omega = \{c_i, \varphi_s, \theta_r, \Lambda\}$ for $i = 1,\dots,N$, $s = 1,\dots,q$ and $r = 1,\dots,p$.

$$w = 1 : p(\Omega^1|f^0)\ then\ p(f^1|\Omega^1)$$

$$w = 2 : p(\Omega^2|f^1)\ then\ p(f^2|\Omega^2)$$

$$\vdots$$

$$w = W : p(\Omega^W|f^{W-1})\ then\ p(f^W|\Omega^W)$$

Kose et al. [2003] propose a multivariate extension. In the case of K factors, at every draw w $K-1$ steps are added, where factor $k, k = 1,\dots K$ is drawn conditionally on the other $K-1$ factors. If $K = 2$ one draw looks like:

$$w = 1 : p(\Omega^1|f_1^0, f_2^0)\ then\ p(f_1^1|\Omega^1, f_2^0)\ then\ p(f_2^1|\Omega^1, f_1^1)$$

The sequence can be generalized to any K.

C.2 Currency Conversions

In this section I explain how I assured that all wheat prices are provided in gold based denominations.

Since the Swedish and German series are explicitly expressed in gold based currencies, they can be directly included in the data set. The enormous data set used in Jacks [2005] has been converted to American dollars with exchange rates from the Global Financial Data (GFD) set. The GFD provides a convenient way to convert historical prices inU.S.S dollars, since all historical exchange rates provided there are U.S. dollar rates. The documentation, however, is not always clear about the Civil War period; i.e. if the respective exchange rate has been tabulated for the dollar in gold or paper. Figure C.1 shows the exchange rates provided by the GFD for the currencies in this study. I also performed indirect checks by comparing Jacks's converted prices with independent price series for the same cities that I converted to gold dollars myself.

Elaborating on Figure C.1, the British pound can be found in both denominations, which is also documented in the GFD notes. Jacks [2005] has used the gold dollar rate as can be seen in Figure C.4 below. The rate shown here is the greenback rate, which coincides almost perfectly with the Norwegian Krone (large Xs).

Both Francs series from Belgium and France coincide one to one with each other and until 1864 with the Pound and the Krone. Thereafter they return to par with the U.S. dollar. The independent series for Brussels is from Verlinden [1972], the one for Toulouse from Drame et al. [1991].

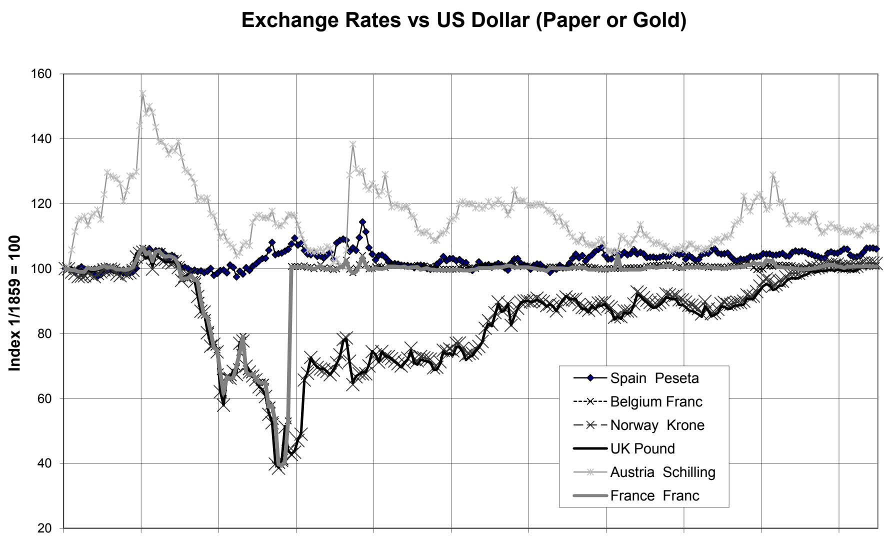
The Spanish Peso deviates somewhat from the dollar, but the large inflationary swings during the Civil War period typical for greenback denominated series can not be found. Thus the impression from independent prices in Burgos [Barquín Gil, 1997] in Figure C.3 is confirmed.

The conclusion to be drawn from the Austrian Schilling exchange rate is similar, although the Schilling deviates violently from the dollar (light grey with small xs). However, the direct comparison to the typical deviations that are exhibited by gold currencies shows that the Austrian Schilling is obviously not expressed in greenbacks. Figure C.2 offers a similar impression.

I checked the price of wheat in New York, too. Finding an U.S. wheat price benchmark which is clearly gold based turns out to be difficult, though. Thus I use an English average price hoping that if U.S. prices are paper based, the deviation from English gold prices would be significantly different from deviations due to trade frictions between the U.S. and the U.K.. The middle panel in C.3 shows that this was no vain endeavor. Although the two prices do not perfectly comove in periods before and after the war, the inflation during the Civil War years is clearly identifiable. I conclude therefore that all U.S. prices are denoted in greenbacks. I repeated the same exercise for the price of wheat in Cincinnati with the same result (not shown).

For the Norwegian prices I have no perfect benchmark, either. I therefore take a Norwegian rye price converted to German gold marks from Statistisches Reichsamt [various years]. It turns out that it is sufficient to show that also the Norwegian prices are con-

Figure C.1: Indexed exchange rates against the U.S. dollar, either greenback or gold dollar, 1859-1879. The series are "close"-values from the Global Financial Database, and identifiable by the code id=4023 (Spain), 4003 (Belgium), 4018 (Norway), 4028 (U.K.), 4002 (Austria), and 4008 (France).



verted to paper money, as a strong unusual deviation occurs during the first half of the 1860s (lower panel in Figure C.3).

The indirect comparison of the U.K. is performed by using the same benchmark as in the U.S. case. It is an average of U.K. prices, so from the Jacks-data set in American dollars I take an unweighted mean of all 12 U.K. cities, and compare it to the Gazette-average. The match is perfect for all years and shows that U.K. prices are converted to gold dollars, not paper money.

I deflate all series that I find to be greenback denominated by the greenback-gold dollar exchange rate[1], leave the gold denominated series as they are, and take this as my new data set.

[1]From Willard et al. [1996], to be found on `http://eh.net/databases/greenback`.

Figure C.2: Comparison between wheat prices from Jacks [2005] (converted into American dollar using the Global Financial Data Set) and suitable gold-denominated price series. Brussels (for Belgium [Verlinden, 1972]), Toulouse (for France [Drame et al., 1991]), Vienna (for Austria-Hungary [Pribram et al., 1938]). 1854-1876.

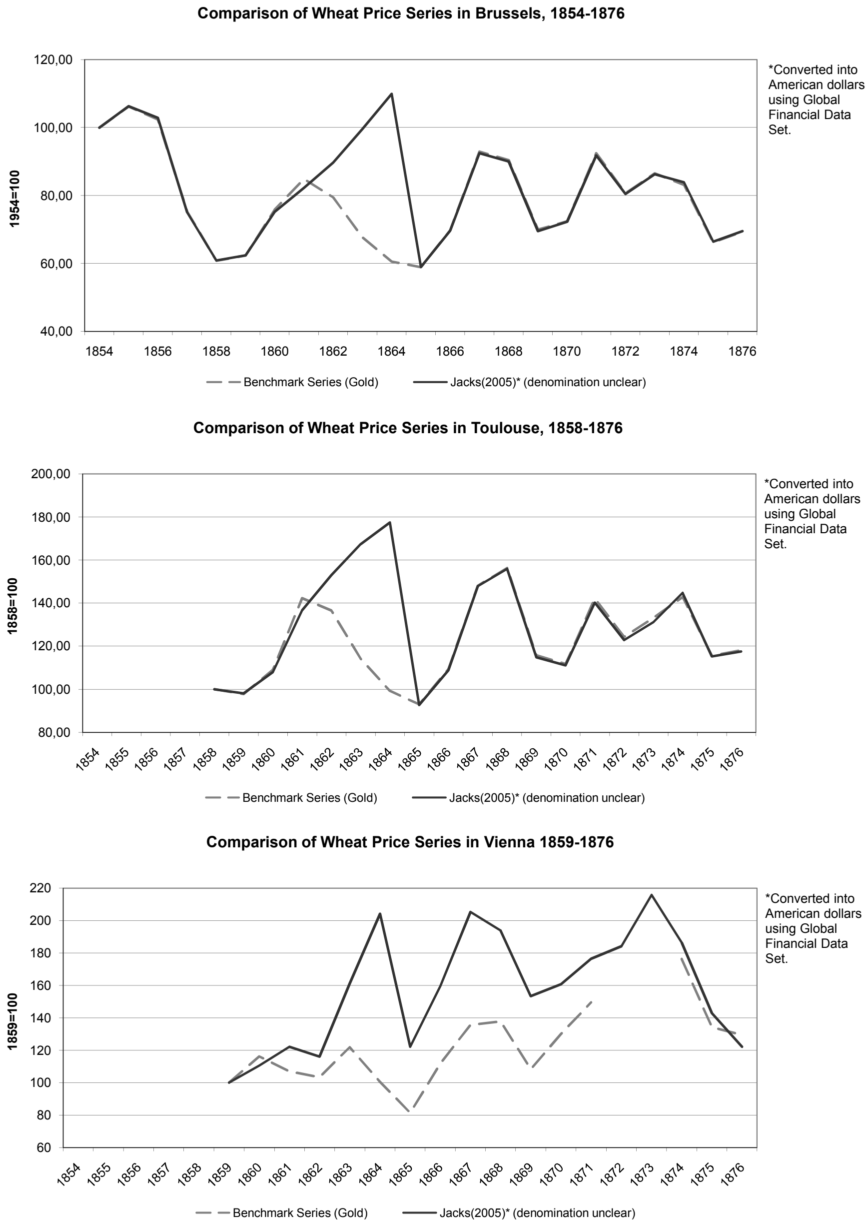
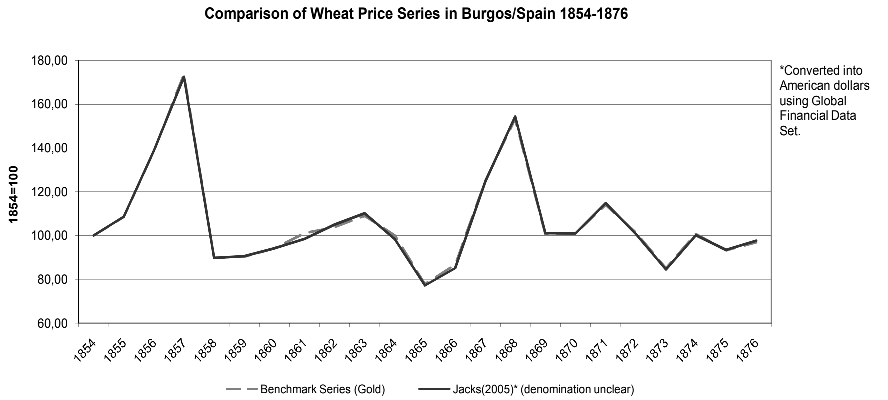
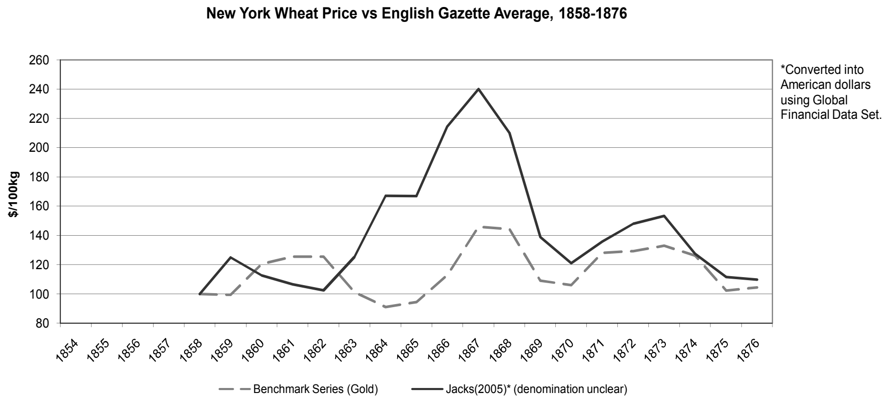


Figure C.3: Comparison between wheat prices from Jacks [2005] (converted into American dollar using the Global Financial Data Set) and suitable gold-denominated price series. Burgos (for Spain [Barquín Gil, 1997]), New York (for the U.S., see Statistical Abstract[Various Years], Bergen (for Norway [Statistisches Reichsamt, various years]). 1854-1876.





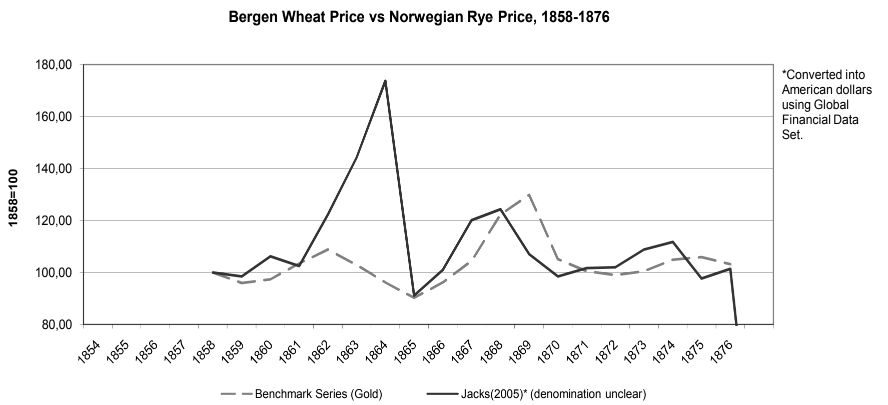
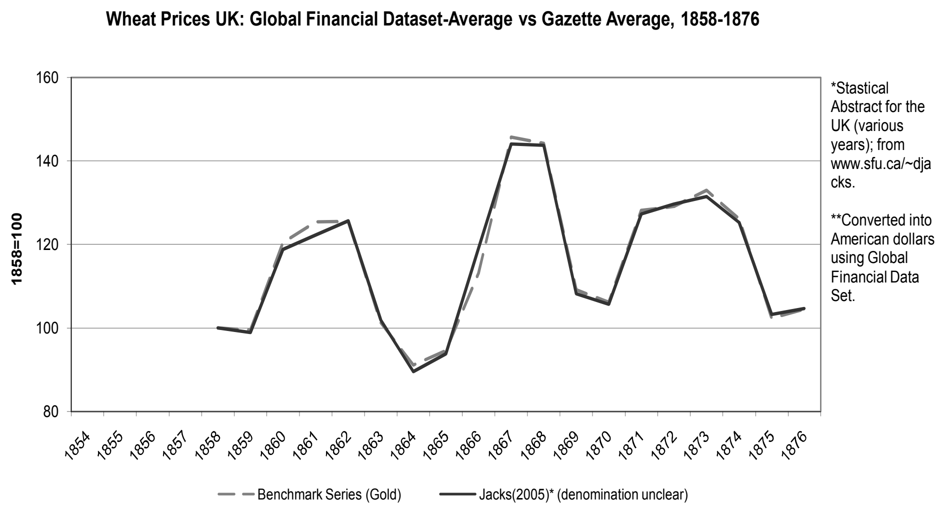


Figure C.4: Comparison between wheat prices from Jacks [2005] (converted into American dollar using the Global Financial Data Set) and suitable gold-denominated price series. Unweighted mean of 12 U.K. price series vs Gazette average price from HM Stationery Office [Various Years]. 1858-1876.



C.3 Full Set of Results

Table C.1: Medians of explained variances. 48 markets, 1806-1855.

	48 Markets. 1806-1855						
	μ		1806-1829			1830-1855	
		World	National	Local	World	National	Local
1	Vienna	0.12	0.76	0.12	0.75	0.13	0.12
2	Lwow	0.24	0.01	0.75	0.43	0.02	0.55
3	Ljubljana	0.21	0.62	0.17	0.62	0.13	0.25
4	Krakow	0.02	0.25	0.73	0.62	0.06	0.32
5	Brugges	0.5	0.44	0.06	0.88	0.09	0.03
6	Ghent	0.59	0.39	0.02	0.89	0.08	0.03
7	Brussels	0.58	0.36	0.06	0.92	0.06	0.02
8	Bayeux	0.66	0.18	0.16	0.73	0.17	0.1
9	Saint-Brieuc	0.58	0.22	0.2	0.8	0.14	0.06
10	Toulouse	0.38	0.48	0.14	0.42	0.52	0.06
11	Bordeaux	0.4	0.52	0.08	0.71	0.26	0.03
12	Chateauroux	0.44	0.44	0.12	0.74	0.2	0.06
13	Mende	0.68	0.24	0.08	0.37	0.39	0.24
14	Barleduc	0.67	0.23	0.1	0.85	0.05	0.1
15	Arras	0.69	0.23	0.08	0.9	0.04	0.06
16	Pau	0.42	0.24	0.34	0.43	0.5	0.07
17	Lyon	0.61	0.33	0.06	0.76	0.11	0.13
18	Paris	0.55	0.32	0.13	0.88	0.05	0.07
19	Berlin	0.16	0.75	0.09	0.92	0.05	0.03
20	Königsberg	0	0.67	0.33	0.82	0.07	0.11
21	München	0.51	0.15	0.34	0.69	0.01	0.3
22	Hamburg	0.18	0.72	0.1	0.83	0.02	0.15
23	London	0.53	0.46	0.01	0.69	0.3	0.01
24	Dover	0.61	0.36	0.03	0.7	0.28	0.02
25	Exeter	0.76	0.15	0.09	0.68	0.27	0.05
26	Gloucester	0.6	0.32	0.08	0.63	0.35	0.02
27	Worcester	0.53	0.41	0.06	0.61	0.36	0.03
28	Cambridge	0.48	0.47	0.05	0.67	0.32	0.01
29	Norwich	0.54	0.41	0.05	0.7	0.29	0.01
30	Leeds	0.31	0.65	0.04	0.64	0.35	0.01
31	Liverpool	0.34	0.58	0.08	0.53	0.39	0.08
32	Manchester	0.29	0.66	0.05	0.61	0.37	0.02
33	Newcastle	0.21	0.64	0.15	0.6	0.36	0.04
34	Carmarthen	0.6	0.21	0.19	0.66	0.22	0.12
35	N.Y. City	0.28	0.54	0.18	0.28	0.6	0.12
36	Philadelphia	0.38	0.55	0.07	0.24	0.73	0.03
37	Alexandria	0.52	0.4	0.08	0.2	0.77	0.03
38	Stockholm	0.06	0.65	0.29	0.16	0.79	0.05
39	Uppsala	0.18	0.47	0.35	0.24	0.71	0.05
40	Södermanland	0.06	0.69	0.25	0.18	0.75	0.07
41	Östergötland	0.08	0.74	0.18	0.21	0.71	0.08
42	Kalmar	0	0.84	0.16	0.16	0.73	0.11
43	Halland	0.01	0.72	0.27	0.13	0.31	0.56
44	Skaraborg	0.01	0.81	0.18	0.13	0.53	0.34
45	Örebro	0.05	0.76	0.19	0.1	0.64	0.26
46	Västmanland	0.14	0.69	0.17	0.11	0.81	0.08
47	Gästrikland	0.05	0.62	0.33	0.19	0.68	0.13
48	Hälsingland	0.01	0.54	0.45	0.09	0.69	0.22

Table C.2: Medians of explained variances. 48 markets, 1856-1907.

	48 Markets. 1856-1907						
	μ		1856-1880			1881-1907	
		World	National	Local	World	National	Local
1	Vienna	0.62	0.28	0.1	0.65	0.33	0.02
2	Lwow	0.81	0	0.19	0.51	0.33	0.16
3	Ljubljana	0.73	0.19	0.08	0.58	0.39	0.03
4	Krakow	0.85	0.06	0.09	0.54	0.43	0.03
5	Brugges	0.64	0.34	0.02	0.89	0.07	0.04
6	Ghent	0.65	0.34	0.01	0.89	0.1	0.01
7	Brussels	0.67	0.32	0.01	0.91	0.09	0
8	Bayeux	0.75	0.2	0.05	0.61	0.3	0.09
9	Saint-Brieuc	0.73	0.23	0.04	0.32	0.35	0.33
10	Toulouse	0.62	0.35	0.03	0.71	0.25	0.04
11	Bordeaux	0.71	0.28	0.01	0.65	0.3	0.05
12	Chateauroux	0.65	0.33	0.02	0.69	0.28	0.03
13	Mende	0.55	0.36	0.09	0.59	0.23	0.18
14	Barleduc	0.68	0.27	0.05	0.63	0.24	0.13
15	Arras	0.75	0.22	0.03	0.69	0.23	0.08
16	Pau	0.61	0.36	0.03	0.66	0.31	0.03
17	Lyon	0.7	0.27	0.03	0.69	0.28	0.03
18	Paris	0.67	0.16	0.17	0.72	0.22	0.06
19	Berlin	0.88	0.04	0.08	0.83	0.13	0.04
20	Königsberg	0.9	0.07	0.03	0.83	0.12	0.05
21	München	0.7	0.01	0.29	0.72	0.11	0.17
22	Hamburg	0.95	0.03	0.02	0.86	0.1	0.04
23	London	0.87	0.12	0.01	0.91	0.08	0.01
24	Dover	0.9	0.09	0.01	0.9	0.07	0.03
25	Exeter	0.95	0.04	0.01	0.92	0.03	0.05
26	Gloucester	0.96	0.04	0	0.95	0.04	0.01
27	Worcester	0.94	0.05	0.01	0.94	0.04	0.02
28	Cambridge	0.91	0.08	0.01	0.92	0.07	0.01
29	Norwich	0.9	0.09	0.01	0.91	0.06	0.03
30	Leeds	0.91	0.07	0.02	0.91	0.07	0.02
31	Liverpool	0.91	0.07	0.02	0.94	0.05	0.01
32	Manchester	0.9	0.08	0.02	0.83	0.09	0.08
33	Newcastle	0.87	0.06	0.07	0.76	0.07	0.17
34	Carmarthen	0.87	0.11	0.02	0.94	0.02	0.04
35	N.Y. City	0.22	0.69	0.09	0.76	0.22	0.02
36	Philadelphia	0.24	0.74	0.02	0.73	0.26	0.01
37	Alexandria	0.14	0.8	0.06	0.7	0.27	0.03
38	Stockholm	0.75	0.14	0.11	0.58	0.35	0.07
39	Uppsala	0.34	0.18	0.48	0.29	0.35	0.36
40	Södermanland	0.78	0.19	0.03	0.34	0.26	0.4
41	Östergötland	0.83	0.14	0.03	0.56	0.38	0.06
42	Kalmar	0.81	0.15	0.04	0.41	0.26	0.33
43	Halland	0.75	0.15	0.1	0.5	0.24	0.26
44	Skaraborg	0.71	0.2	0.09	0.63	0.21	0.16
45	Örebro	0.76	0.19	0.05	0.35	0.32	0.33
46	Västmanland	0.79	0.18	0.03	0.52	0.4	0.08
47	Gästrikland	0.63	0.03	0.34	0.49	0.13	0.38
48	Hälsingland	0.2	0.03	0.77	0.47	0.11	0.42

Table C.3: Standard deviations of explained variances. 48 markets, 1806-1907.

	48 Markets, 1806-1855						
	σ	1806-1829			1830-1855		
		World	National	Local	World	National	Local
1	Vienna	0.03	0.11	0.10	0.03	0.08	0.07
2	Lwow	0.05	0.03	0.05	0.04	0.13	0.12
3	Ljubljana	0.05	0.10	0.09	0.03	0.10	0.09
4	Krakow	0.03	0.09	0.09	0.04	0.09	0.08
5	Brugges	0.15	0.15	0.02	0.03	0.03	0.01
6	Ghent	0.15	0.15	0.01	0.03	0.03	0.01
7	Brussels	0.16	0.16	0.02	0.03	0.03	0.01
8	Bayeux	0.19	0.19	0.03	0.05	0.05	0.01
9	Saint-Brieuc	0.18	0.18	0.03	0.04	0.04	0.01
10	Toulouse	0.16	0.17	0.05	0.05	0.05	0.02
11	Bordeaux	0.17	0.18	0.03	0.05	0.05	0.01
12	Chateauroux	0.18	0.19	0.03	0.05	0.05	0.01
13	Mende	0.17	0.17	0.02	0.04	0.05	0.03
14	Barleduc	0.17	0.17	0.02	0.04	0.03	0.01
15	Arras	0.19	0.19	0.02	0.03	0.03	0.01
16	Pau	0.10	0.11	0.04	0.05	0.05	0.02
17	Lyon	0.17	0.17	0.02	0.04	0.04	0.01
18	Paris	0.18	0.19	0.03	0.04	0.03	0.01
19	Berlin	0.08	0.09	0.05	0.02	0.02	0.02
20	Königsberg	0.02	0.06	0.06	0.03	0.05	0.03
21	München	0.10	0.09	0.04	0.03	0.03	0.05
22	Hamburg	0.07	0.09	0.05	0.03	0.04	0.02
23	London	0.18	0.18	0.01	0.03	0.03	0.01
24	Dover	0.19	0.19	0.01	0.03	0.03	0.01
25	Exeter	0.20	0.19	0.02	0.04	0.03	0.01
26	Gloucester	0.20	0.20	0.02	0.03	0.03	0.01
27	Worcester	0.19	0.19	0.01	0.04	0.04	0.01
28	Cambridge	0.17	0.17	0.01	0.03	0.03	0.01
29	Norwich	0.18	0.18	0.01	0.03	0.03	0.01
30	Leeds	0.13	0.13	0.02	0.04	0.03	0.01
31	Liverpool	0.15	0.15	0.01	0.03	0.04	0.01
32	Manchester	0.13	0.13	0.01	0.03	0.03	0.01
33	Newcastle	0.09	0.09	0.03	0.04	0.04	0.01
34	Carmarthen	0.18	0.17	0.02	0.03	0.03	0.01
35	N.Y. City	0.07	0.11	0.09	0.03	0.03	0.02
36	Philadelphia	0.06	0.10	0.08	0.03	0.03	0.02
37	Alexandria	0.07	0.09	0.06	0.03	0.03	0.02
38	Stockholm	0.03	0.04	0.03	0.03	0.03	0.01
39	Uppsala	0.05	0.06	0.04	0.03	0.03	0.01
40	Södermanland	0.02	0.06	0.05	0.03	0.03	0.01
41	Östergötland	0.03	0.05	0.03	0.03	0.04	0.01
42	Kalmar	0.06	0.05	0.04	0.03	0.03	0.01
43	Halland	0.06	0.06	0.05	0.02	0.03	0.02
44	Skaraborg	0.03	0.04	0.03	0.02	0.03	0.02
45	Örebro	0.02	0.04	0.03	0.02	0.03	0.02
46	Västmanland	0.04	0.06	0.03	0.02	0.03	0.01
47	Gästrikland	0.03	0.04	0.04	0.03	0.04	0.02
48	Hälsingland	0.07	0.06	0.06	0.02	0.03	0.02

Table C.4: Standard deviations of explained variances. 48 markets, 1806-1907.

	48 Markets, 1856-1907						
	σ		1856-1880			1881-1907	
		World	National	Local	World	National	Local
1	Vienna	0.03	0.06	0.05	0.06	0.06	0.01
2	Lwow	0.04	0.02	0.03	0.06	0.06	0.02
3	Ljubljana	0.03	0.04	0.03	0.06	0.07	0.01
4	Krakow	0.03	0.03	0.02	0.07	0.08	0.01
5	Brugges	0.03	0.03	0.01	0.04	0.03	0.01
6	Ghent	0.03	0.03	0.01	0.03	0.03	0.01
7	Brussels	0.03	0.03	0.01	0.04	0.03	0.01
8	Bayeux	0.03	0.03	0.01	0.07	0.07	0.01
9	Saint-Brieuc	0.03	0.03	0.01	0.05	0.06	0.02
10	Toulouse	0.03	0.03	0.01	0.05	0.05	0.01
11	Bordeaux	0.03	0.03	0.01	0.06	0.06	0.01
12	Chateauroux	0.03	0.03	0.01	0.08	0.08	0.01
13	Mende	0.04	0.04	0.01	0.05	0.05	0.02
14	Barleduc	0.03	0.03	0.01	0.08	0.09	0.02
15	Arras	0.03	0.03	0.01	0.08	0.08	0.01
16	Pau	0.03	0.03	0.01	0.06	0.06	0.01
17	Lyon	0.03	0.03	0.01	0.07	0.07	0.01
18	Paris	0.03	0.03	0.01	0.07	0.07	0.01
19	Berlin	0.03	0.03	0.02	0.05	0.05	0.01
20	Königsberg	0.05	0.05	0.02	0.04	0.04	0.02
21	München	0.03	0.03	0.04	0.05	0.06	0.03
22	Hamburg	0.04	0.04	0.01	0.05	0.05	0.01
23	London	0.05	0.05	0.01	0.08	0.08	0.00
24	Dover	0.04	0.04	0.00	0.08	0.08	0.00
25	Exeter	0.04	0.04	0.00	0.06	0.06	0.01
26	Gloucester	0.04	0.04	0.00	0.08	0.07	0.01
27	Worcester	0.05	0.04	0.00	0.07	0.07	0.00
28	Cambridge	0.05	0.04	0.00	0.08	0.08	0.00
29	Norwich	0.04	0.04	0.00	0.09	0.09	0.01
30	Leeds	0.05	0.05	0.00	0.06	0.06	0.01
31	Liverpool	0.05	0.05	0.00	0.07	0.07	0.00
32	Manchester	0.05	0.05	0.00	0.07	0.06	0.01
33	Newcastle	0.04	0.04	0.01	0.06	0.06	0.02
34	Carmarthen	0.05	0.05	0.01	0.07	0.06	0.01
35	N.Y. City	0.02	0.03	0.02	0.04	0.04	0.01
36	Philadelphia	0.02	0.03	0.02	0.05	0.05	0.01
37	Alexandria	0.02	0.03	0.03	0.04	0.04	0.01
38	Stockholm	0.04	0.04	0.01	0.07	0.07	0.02
39	Uppsala	0.03	0.04	0.03	0.03	0.04	0.04
40	Södermanland	0.04	0.04	0.01	0.07	0.10	0.04
41	Östergötland	0.04	0.04	0.01	0.06	0.06	0.02
42	Kalmar	0.04	0.04	0.01	0.06	0.06	0.02
43	Halland	0.04	0.04	0.01	0.06	0.06	0.02
44	Skaraborg	0.05	0.05	0.01	0.06	0.05	0.02
45	Örebro	0.04	0.04	0.01	0.03	0.05	0.03
46	Västmanland	0.05	0.04	0.01	0.05	0.05	0.02
47	Gästrikland	0.04	0.03	0.01	0.05	0.05	0.02
48	Hälsingland	0.02	0.02	0.02	0.04	0.04	0.02

Table C.5: Medians of explained variances. 60 markets, 1830-1907.

	60 Markets, 1830-1907									
	μ		1830-1855			1856-1880			1881-1907	
		World	National	Local	World	National	Local	World	National	Local
1	Vienna	0.73	0.06	0.21	0.62	0.28	0.1	0.63	0.35	0.02
2	Lwow	0.38	0.11	0.51	0.69	0.01	0.3	0.51	0.36	0.13
3	Ljubljana	0.62	0.09	0.29	0.74	0.19	0.07	0.55	0.42	0.03
4	Krakow	0.56	0.1	0.34	0.85	0.06	0.09	0.52	0.46	0.02
5	Brugges	0.92	0.05	0.03	0.6	0.37	0.03	0.89	0.06	0.05
6	Ghent	0.93	0.04	0.03	0.61	0.38	0.01	0.9	0.09	0.01
7	Brussels	0.95	0.03	0.02	0.62	0.36	0.02	0.92	0.07	0.01
8	Bayeux	0.76	0.13	0.11	0.75	0.21	0.04	0.64	0.29	0.07
9	Saint-Brieuc	0.84	0.11	0.05	0.71	0.25	0.04	0.34	0.36	0.3
10	Toulouse	0.47	0.46	0.07	0.53	0.45	0.02	0.73	0.2	0.07
11	Bordeaux	0.76	0.21	0.03	0.63	0.35	0.02	0.67	0.28	0.05
12	Chateauroux	0.78	0.15	0.07	0.59	0.38	0.03	0.7	0.27	0.03
13	Mende	0.41	0.35	0.24	0.43	0.51	0.06	0.62	0.18	0.2
14	Barleduc	0.88	0.02	0.1	0.65	0.3	0.05	0.66	0.22	0.12
15	Arras	0.93	0.02	0.05	0.74	0.24	0.02	0.74	0.18	0.08
16	Pau	0.49	0.45	0.06	0.52	0.45	0.03	0.7	0.27	0.03
17	Lyon	0.81	0.07	0.12	0.68	0.3	0.02	0.69	0.26	0.05
18	Paris	0.9	0.03	0.07	0.65	0.18	0.17	0.75	0.21	0.04
19	Berlin	0.92	0.05	0.03	0.79	0.14	0.07	0.83	0.14	0.03
20	Königsberg	0.78	0.15	0.07	0.71	0.25	0.04	0.83	0.11	0.06
21	München	0.72	0.01	0.27	0.66	0.03	0.31	0.74	0.09	0.17
22	Hamburg	0.85	0.01	0.14	0.8	0.16	0.04	0.88	0.09	0.03
23	London	0.68	0.31	0.01	0.7	0.29	0.01	0.92	0.07	0.01
24	Dover	0.7	0.28	0.02	0.75	0.23	0.02	0.9	0.06	0.04
25	Exeter	0.69	0.27	0.04	0.8	0.18	0.02	0.93	0.02	0.05
26	Gloucester	0.63	0.35	0.02	0.79	0.19	0.02	0.98	0.01	0.01
27	Worcester	0.62	0.35	0.03	0.75	0.23	0.02	0.97	0.02	0.01
28	Cambridge	0.67	0.32	0.01	0.72	0.27	0.01	0.95	0.03	0.02
29	Norwich	0.71	0.29	0	0.74	0.25	0.01	0.94	0.02	0.04
30	Leeds	0.64	0.35	0.01	0.72	0.26	0.02	0.92	0.05	0.03
31	Liverpool	0.53	0.39	0.08	0.73	0.25	0.02	0.96	0.03	0.01
32	Manchester	0.6	0.38	0.02	0.71	0.26	0.03	0.82	0.12	0.06
33	Newcastle	0.61	0.34	0.05	0.7	0.23	0.07	0.75	0.05	0.2
34	Carmarthen	0.66	0.22	0.12	0.69	0.28	0.03	0.92	0.02	0.06
35	N.Y. City	0.33	0.56	0.11	0.2	0.72	0.08	0.78	0.2	0.02
36	Philadelphia	0.3	0.67	0.03	0.17	0.81	0.02	0.78	0.21	0.01
37	Cincinnatti	0.13	0.64	0.23	0.45	0.07	0.48	0.66	0.31	0.03
38	Alexandria	0.27	0.7	0.03	0.1	0.84	0.06	0.75	0.22	0.03
39	Stockholm	0.12	0.84	0.04	0.62	0.27	0.11	0.57	0.36	0.07
40	Uppsala	0.2	0.76	0.04	0.28	0.23	0.49	0.29	0.36	0.35
41	Södermanland	0.14	0.8	0.06	0.6	0.36	0.04	0.35	0.24	0.41
42	Östergötland	0.16	0.75	0.09	0.65	0.31	0.04	0.56	0.38	0.06
43	Kalmar	0.13	0.76	0.11	0.66	0.3	0.04	0.39	0.28	0.33
44	Halland	0.11	0.29	0.6	0.62	0.28	0.1	0.47	0.27	0.26
45	Skaraborg	0.09	0.59	0.32	0.49	0.43	0.08	0.6	0.23	0.17
46	Örebro	0.07	0.69	0.24	0.57	0.38	0.05	0.34	0.34	0.32
47	Västmanland	0.08	0.84	0.08	0.59	0.38	0.03	0.51	0.42	0.07
48	Gästrikland	0.16	0.72	0.12	0.44	0.19	0.37	0.49	0.12	0.39
49	Hälsingland	0.07	0.7	0.23	0.12	0.1	0.78	0.44	0.13	0.43
50	Bergen	0.93	0.01	0.06	0.41	0.55	0.04	0.34	0.5	0.16
51	Christiania (Oslo)	0.71	0.15	0.14	0.16	0.76	0.08	0.12	0.67	0.21
52	Burgos	0.03	0.57	0.4	0.01	0.61	0.38	0.09	0.79	0.12
53	Cordoba	0.43	0.33	0.24	0.24	0.5	0.26	0.52	0.27	0.21
54	Gerona	0.09	0.48	0.43	0.01	0.75	0.24	0.04	0.8	0.16
55	Granada	0.21	0.66	0.13	0.01	0.78	0.21	0.34	0.51	0.15
56	Lerida	0.12	0.42	0.46	0.17	0.63	0.2	0.02	0.08	0.9
57	Oviedo	0.09	0.35	0.56	0.03	0.78	0.19	0.43	0.33	0.24
58	Segovia	0.14	0.64	0.22	0.01	0.86	0.13	0.45	0.25	0.3
59	Zaragoza	0.32	0.21	0.47	0.08	0.68	0.24	0.08	0.25	0.67
60	Santander	0.07	0.45	0.48	0.06	0.82	0.12	0.17	0.38	0.45

Table C.6: Standard deviations of explained variances. 60 markets, 1830-1907.

60 Markets, 1830-1907										
	σ	1830-1855			1856-1880			1881-1907		
		World	National	Local	World	National	Local	World	National	Local
1	Vienna	0.02	0.07	0.07	0.08	0.09	0.06	0.02	0.02	0.01
2	Lwow	0.02	0.14	0.13	0.12	0.07	0.07	0.02	0.02	0.02
3	Ljubljana	0.02	0.07	0.06	0.08	0.09	0.03	0.02	0.03	0.01
4	Krakow	0.02	0.09	0.08	0.08	0.08	0.03	0.02	0.02	0.01
5	Brugges	0.02	0.02	0.01	0.1	0.1	0.01	0.01	0.01	0.01
6	Ghent	0.02	0.02	0.01	0.1	0.1	0.01	0.01	0.01	0.01
7	Brussels	0.01	0.01	0.01	0.11	0.11	0.01	0.01	0.01	0.00
8	Bayeux	0.02	0.02	0.01	0.09	0.09	0.01	0.02	0.02	0.01
9	Saint-Brieuc	0.02	0.02	0.01	0.1	0.1	0.01	0.01	0.03	0.02
10	Toulouse	0.02	0.03	0.02	0.12	0.12	0.01	0.02	0.02	0.01
11	Bordeaux	0.02	0.02	0.01	0.11	0.11	0.01	0.02	0.02	0.01
12	Chateauroux	0.02	0.02	0.01	0.11	0.11	0.01	0.02	0.02	0.01
13	Mende	0.02	0.04	0.03	0.11	0.13	0.02	0.01	0.02	0.02
14	Barleduc	0.02	0.01	0.01	0.1	0.1	0.01	0.02	0.02	0.01
15	Arras	0.02	0.01	0.01	0.1	0.1	0.01	0.01	0.02	0.01
16	Pau	0.02	0.03	0.02	0.11	0.12	0.01	0.02	0.02	0.01
17	Lyon	0.02	0.02	0.01	0.1	0.1	0.01	0.02	0.02	0.01
18	Paris	0.02	0.01	0.01	0.08	0.08	0.01	0.01	0.02	0.01
19	Berlin	0.01	0.02	0.01	0.12	0.12	0.02	0.02	0.03	0.02
20	Königsberg	0.02	0.04	0.04	0.15	0.15	0.02	0.02	0.02	0.01
21	München	0.02	0.02	0.03	0.08	0.07	0.03	0.02	0.03	0.02
22	Hamburg	0.02	0.01	0.02	0.14	0.14	0.02	0.01	0.02	0.01
23	London	0.02	0.02	0.00	0.14	0.14	0.01	0.03	0.03	0.00
24	Dover	0.02	0.02	0.00	0.13	0.13	0.01	0.03	0.03	0.01
25	Exeter	0.02	0.02	0.00	0.14	0.13	0.01	0.02	0.01	0.00
26	Gloucester	0.02	0.02	0.00	0.14	0.14	0.01	0.01	0.01	0.00
27	Worcester	0.02	0.02	0.00	0.14	0.14	0.01	0.02	0.02	0.00
28	Cambridge	0.02	0.02	0.00	0.15	0.15	0.01	0.02	0.02	0.00
29	Norwich	0.02	0.02	0.00	0.14	0.14	0.01	0.02	0.02	0.00
30	Leeds	0.02	0.02	0.00	0.15	0.15	0.01	0.02	0.02	0.01
31	Liverpool	0.02	0.02	0.01	0.15	0.15	0.01	0.02	0.02	0.00
32	Manchester	0.02	0.02	0.00	0.15	0.15	0.01	0.04	0.04	0.02
33	Newcastle	0.02	0.02	0.00	0.14	0.14	0.01	0.03	0.03	0.01
34	Carmarthen	0.02	0.02	0.00	0.14	0.14	0.01	0.02	0.02	0.01
35	N.Y. City	0.02	0.03	0.02	0.03	0.04	0.02	0.02	0.02	0.01
36	Philadelphia	0.02	0.02	0.02	0.05	0.05	0.02	0.02	0.02	0.01
37	Cincinnatti	0.01	0.03	0.03	0.04	0.02	0.04	0.02	0.02	0.01
38	Alexandria	0.02	0.02	0.02	0.03	0.04	0.02	0.02	0.02	0.01
39	Stockholm	0.01	0.02	0.01	0.12	0.12	0.01	0.03	0.03	0.02
40	Uppsala	0.01	0.02	0.01	0.06	0.07	0.02	0.02	0.04	0.03
41	Södermanland	0.01	0.02	0.01	0.14	0.14	0.01	0.02	0.04	0.03
42	Östergötland	0.01	0.02	0.01	0.14	0.14	0.01	0.02	0.03	0.02
43	Kalmar	0.01	0.02	0.01	0.13	0.13	0.01	0.02	0.03	0.02
44	Halland	0.01	0.02	0.02	0.12	0.12	0.01	0.02	0.03	0.02
45	Skaraborg	0.01	0.02	0.02	0.15	0.16	0.02	0.02	0.02	0.02
46	Örebro	0.01	0.02	0.02	0.14	0.14	0.01	0.02	0.04	0.03
47	Västmanland	0.01	0.02	0.01	0.15	0.15	0.01	0.02	0.03	0.02
48	Gästrikland	0.01	0.02	0.02	0.13	0.13	0.02	0.02	0.03	0.02
49	Hälsingland	0.01	0.02	0.02	0.05	0.06	0.02	0.02	0.03	0.02
50	Bergen	0.01	0.01	0.01	0.09	0.09	0.04	0.02	0.1	0.10
51	Christiania (Oslo)	0.02	0.09	0.08	0.05	0.07	0.05	0.01	0.12	0.12
52	Burgos	0.01	0.07	0.07	0.04	0.05	0.04	0.01	0.05	0.05
53	Cordoba	0.02	0.04	0.04	0.1	0.1	0.04	0.02	0.03	0.02
54	Gerona	0.01	0.06	0.06	0.03	0.04	0.03	0.01	0.05	0.05
55	Granada	0.02	0.05	0.05	0.03	0.05	0.04	0.02	0.03	0.03
56	Lerida	0.01	0.06	0.06	0.1	0.1	0.03	0	0.03	0.03
57	Oviedo	0.01	0.07	0.06	0.05	0.07	0.04	0.03	0.04	0.03
58	Segovia	0.01	0.05	0.04	0.03	0.04	0.03	0.02	0.03	0.03
59	Zaragoza	0.02	0.04	0.04	0.06	0.07	0.03	0.01	0.04	0.05
60	Santander	0.01	0.07	0.07	0.06	0.08	0.03	0.02	0.05	0.04

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Selbständigkeitserklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, 26. August 2008